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Shedding Light on the Shortness of Sight:

Myopia Prevalence Among School Students and the Usage of Light Meters in the Study of Light-Myopia Associations

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All we have to decide is what to do with the time that is given us.

J. R. R. Tolkien

Abstract

The global rise in myopia prevalence sets off certain alarm bells, as myopia not only imposes a substantial economic and financial burden on affected individuals and the public, but can also entail further negative consequences, such as secondary pathologies as well as reduced quality of life and educational outcomes. The development of the most common type of myopia is connected to both school age as a critical period and bright light exposure as a key protective factor. Accordingly, timely public health interventions need up-to-date information on myopia prevalence and its associations, as well as the relationship with bright light exposure, which is often investigated with wearable light meters.

This dissertation addresses in six studies three main research objectives to fill crucial gaps in myopia research: (1) providing up-to-date myopia prevalence data for German youth, (2) evaluating the utility of online questionnaires in epidemiological research, and (3) advancing methodological understanding of light meter use in myopia research.

In Study 1, refractive measurements of > 1,500 school students in Germany revealed a myopia prevalence of 8.4% in primary school students (mean age 9.30 years) and 19.5% in secondary school students (mean age 14.99 years) as well as a large proportion of uncorrected myopia (51.2% and 43.3%, respectively). Study 2 evaluated five recruitment strategies for an online parent questionnaire on children's spectacle ownership, identifying varying (dis)advantages per strategy related to aspects such as representativeness, efficiency and costs. Study 3 analyzed the questionnaire data from > 1,700 children, demonstrating discrepancies in prevalence rates of corrected myopia compared to direct measurements, thereby indicating biases in the questionnaire data.

A comprehensive literature review in Study 4 examined the use of various wearable light meters in myopia research, revealing significant variability in device specifications and research methodologies, which likely contributes to inconsistent findings in the field. Study 5 directly compared the performance of multiple light meters worn simultaneously, showing similar light exposure patterns but substantial differences in absolute lux values and in the frequently investigated distinction of indoor and outdoor environments. Study 6 explored the development of a custom-made light meter, concluding that while feasible, commercial devices may be more practical for most research needs.

This dissertation's findings highlight the necessity for continuous monitoring of myopia prevalence, especially uncorrected myopia, and emphasize the importance of methodological rigor in research on light exposure and myopia. Recommendations include routine refractive screenings in schools and careful consideration of light meter selection and methodology in future studies on light-myopia associations. These insights address both future research efforts as well as public health strategies aiming at myopia.

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List of Abbreviations

AOA	American Optometric Association
BIC	Bayesian Information Criterion
CIE	International Commission on Illumination (Commission Internationale de l'Eclairage)
D	diopters
GPS	global positioning system
ICC	intraclass correlation coefficient
GWAS	genome-wide association study
IO-cut-off	indoor-outdoor-cut-off
IR	infrared
KiGGS	German Health Interview and Examination Survey for Children and Adolescents
LMA	light-myopia associations
MR	Mendelian randomization
MTurk	Amazon Mechanical Turk
ROC	receiver operating characteristic
SER	spherical equivalent refraction (sphere + ½ cylinder)
SES	socioeconomic status
SNP	single nucleotide polymorphism
UMTS	Universal Mobile Telecommunications System
UV	ultraviolet
WHO	World Health Organization

1. General Introduction

With rates of myopia (short-sightedness, nearsightedness) rising globally, urgent attention is required to investigate its prevalence, causes, and avenues for prevention and intervention. Myopia can lead to severe secondary pathologies, which can even result in blindness (Morgan et al., 2012; Rose et al., 2001). Furthermore, it is associated with considerable financial costs both for those affected and the healthcare system (Flitcroft, 2012; Holden et al., 2014; Rose et al., 2001). The World Health Organization (WHO) considers myopia to be among the five most important visual disorders whose control is a high priority (Lagrèze & Schaeffel, 2017), and unless counter-measures are taken, 50% of the world's population is expected to be myopic by 2050 (Holden et al., 2016).

Prevalence rates vary between regions (Baird et al., 2020; Xiang & Zou, 2020), and for many parts of the world – including Europe – there are only few studies reporting current prevalence data (for reviews, see: Grzybowski et al., 2020; Xiang & Zou, 2020). The onset of myopia often occurs during school age (Morgan & Rose, 2005; Spillmann, 2020). Furthermore, diagnosing and fully correcting myopia are not only important to allow for the best possible vision, but also to slow down myopia progression (Logan & Wolffsohn, 2020), which in turn might prevent secondary pathologies. Hence, especially in children and adolescents, current prevalence rates of myopia and uncorrected myopia as well as knowledge about associated factors are highly relevant and can inform prevention and intervention strategies. Using autorefraction measurements, I investigate prevalence rates of myopia and uncorrected myopia as well as associated factors in German school students. I also investigate online questionnaires as a less resource-intensive means, compared to direct autorefraction measurements, for estimating aspects of myopia prevalence (development).

To effectively prevent or slow down myopia progression, it is crucial to investigate modifiable factors influencing its development. One such factor is light exposure, which has – especially in recent years – often been investigated by measuring participants' real-life light exposure via wearable light meters. Thereby, myopia has repeatedly been associated to reduced bright/outdoor light exposure (Mirhajianmoghadam et al., 2021; Read et al., 2014, 2015; Wu et al., 2018). However, the results are not unambiguous, as some studies do not detect such associations (Dharani et al., 2012; M. Li et al., 2021). The variation in results may be influenced by differences between the light meters and other study parameters. To advance the understanding of light-myopia associations, methodological considerations regarding light meters and other study parameters are crucial. Thus, I review and compare light meters employed in studies on light-myopia associations as well as the methodology of said studies. I also describe the development and testing of a custom device specifically designed for measuring light in the investigation of light-myopia associations.

1.1. Myopia Epidemiology

Myopia is a refractive error primarily characterized by blurred vision when observing objects at a distance, while close objects can be seen clearly. The reason for this lies in how incident light is focused in the eye. While there are also other refractive errors (see Table 1.1), I will focus on myopia and hyperopia (farsightedness) to briefly explain how light is focused in emmetropic (normally-sighted) versus both hyperopic and myopic eyes: In emmetropic eyes, the essentially parallel rays of light from distant objects are refracted by the cornea and lens so that they are focused on the retinal photoreceptors, which is necessary for the formation of a clear image. Objects at a closer distance have their focal point behind the retina in normal vision; however, through accommodation, they can be brought into focus. Accommodation is the eye's ability to adjust the optical power of the lens: To bring closer objects into focus, its optical power can be increased (Morgan et al., 2012). In hyperopia, the focal point of objects lies behind the retina, primarily because the eyeball is too short (Morgan et al., 2012; Strang et al., 1998). Through accommodation, hyperopic eyes can bring (distant) objects into focus to some extent (Morgan et al., 2012), and thus do not necessarily always need (full) refractive correction.

Table 1.1

Overview of Refractive Errors

refractive error	primary symptom
myopia	blurred vision when observing distant objects
hyperopia	blurred vision when observing nearby objects
astigmatism	blurred vision at any distance
presbyopia	blurred vision when observing close objects, developing with age

Conversely, in myopic eyes, the focal point of light falls in front of the retina for distant objects, because the eyeball is too long or due to an abnormally high optical power of cornea and/or lens (Flitcroft et al., 2019; Morgan et al., 2012). This cannot be adjusted for via accommodation. For closer objects, the focal point of light falls on the retina. Even closer objects have their focal point behind the retina and can be brought into focus by accommodation. Myopia is thus optically corrected with concave lenses, moving the focal point of distant objects onto the retina (Morgan et al., 2012). Figure 1.1 presents schematic depictions of how light from distant and near objects is focused in the emmetropic, hyperopic and myopic eye.

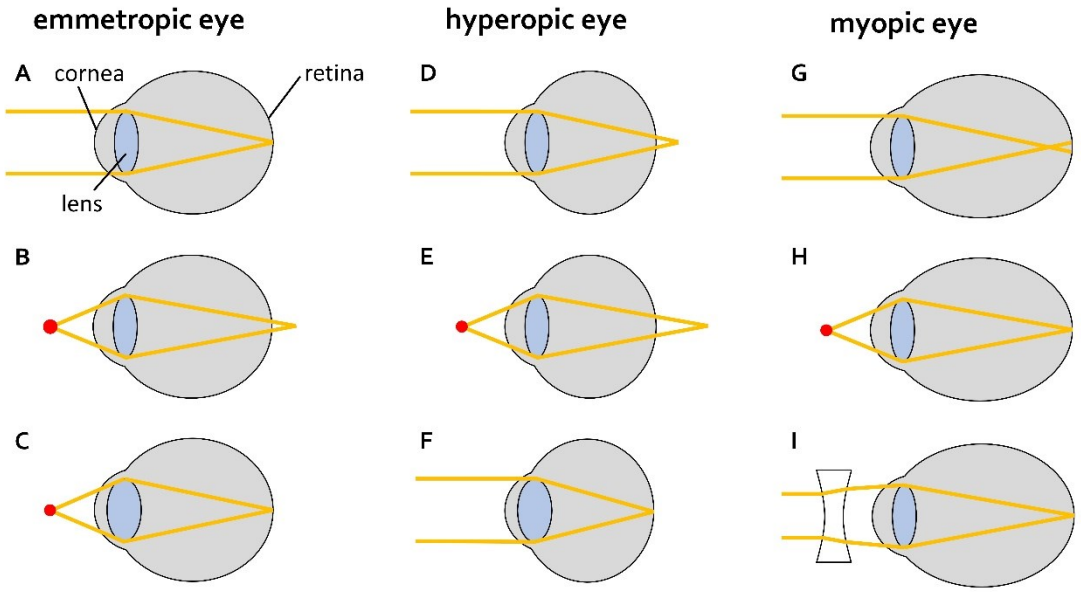

Figure 1.1. Schematic depictions of light from distant and near objects being focused in the emmetropic, hyperopic and myopic eye. Hyperopia (myopia) is depicted via a shortened (elongated) eyeball. Instead, the refractive errors can also be caused by altered optical power of cornea and/or lens. (A) Rays of light from distant objects are focused on the retina in emmetropic eyes, while (B) rays of light from near objects are focused behind the retina, but (C) are brought into focus via accommodation (thickening of the lens). (D) In hyperopic eyes, rays of light from distant objects are focused behind the retina, and (E) rays of light from near objects are also focused behind the retina. (F) Accommodation can bring the focal point of distant objects onto the retina in hyperopic eyes, and thus enable clear distance vision. Convex lenses are used to shift the focal point of nearer objects onto the retina (not depicted). (G) In myopic eyes, rays of light from distant objects are focused in front of the retina, while (H) rays of light from near objects are focused on the retina, enabling clear near vision. (I) Concave lenses are used to shift the focal point of distant objects back onto the retina, as starting from the unaccommodated state, the lens can only thicken to shift the focal point forward and not flatten to shift it back. Thus, accommodation cannot compensate for myopia.

1.1.1. Types of Myopia

Myopia is commonly classified based on the causes for the shifted focal point: *Refractive myopia* is caused by an abnormally high optical power of cornea and/or lens. The far more common *axial myopia* is caused by increased axial length – i.e., the eyeball is too long in relation to the refractive power of cornea and lens (Flitcroft et al., 2019). Axial myopia usually develops during childhood or adolescence: Most children are born hyperopic and during the first years of life, a process called emmetropization occurs. Thereby, the eye's axial length is matched to the optical power of cornea and lens to induce emmetropia.

Emmetropia denotes the normal refractive state in which, when accommodation is relaxed, rays of light from distant objects are accurately focused on the retina and can thus be seen clearly. Emmetropization is an active process, which, among others, involves axial elongation – i.e., eye growth (Baird et al., 2020; Morgan & Rose, 2005). Basically, axial myopia develops if axial elongation continues despite emmetropia having already been reached through emmetropization (Baird et al., 2020; Morgan et al., 2012).

Due to its onset during school age, axial myopia is also known as school myopia (or juvenile myopia). There are varying definitions regarding the age range for school myopia onset and progression. It has, for example, been described to appear between the ages of 9 and 11 years and to progress up until late adolescence or early twenties (Gilmartin, 2004). A somewhat broader definition describes school myopia to appear between 8 and 14 years of age, and to potentially progress up until circa 30 years of age (Morgan & Rose, 2005). Regardless of the exact age of school myopia onset, the relevance of monitoring school-aged children with regard to myopia is evident.

1.1.2. Quantification and Degrees of Myopia

To quantify the severity of myopia, the spherical equivalent refraction (SER; sphere + ½ cylinder) is often used. Generally, the spherical value specifies the degree of myopia or hyperopia, which is equal across all meridians of the eye. The cylindrical value specifies the degree of astigmatism – i.e., uneven curvature of the cornea or lens. By merging the spherical and cylindrical components of an eye's refractive status, the SER is useful to both classify and quantify refractive errors via a singular value, e.g. for research purposes. An SER of zero indicates perfect emmetropia, a negative SER indicates myopic, and a positive SER hyperopic refractive status.

Myopia is most commonly defined as an SER of < -0.5D (diopters) or ≤ -0.5D, although there is no standardized definition. Furthermore, researchers do not always choose this threshold in their investigations, and depending on the nature of the study, others may be more appropriate (Flitcroft et al., 2019). In addition, a distinction is usually made between different degrees of myopia. *Low myopia* and *high myopia* are often differentiated – but again, there is no standardized definition for either one (Flitcroft et al., 2019). Flitcroft et al. (2019) propose to classify low myopia as ≤ -0.5D SER and > -6.00D SER and high myopia as ≤ -6.00D SER, both while the accommodation is relaxed. The WHO, on the other hand, recommends distinguishing myopia (≤ -0.5D SER in either eye) and high myopia (≤ -5.00D SER in either eye; World Health Organization, 2016). However, Flitcroft et al. (2019) point out that the utilization of "either eye" in the definition is problematic for studies in which individual eyes are analyzed.

1.1.3. Potential Consequences of Myopia

Optical correction serves as a generally straightforward remedy for the poor vision associated with refractive errors – yet, uncorrected refractive errors are still common and have been identified as the principal global cause of visual impairment, including blindness (Pascolini & Mariotti, 2012). In their review, Rudnicka et al. (2016) describe myopia as the predominant cause of correctable visual impairment in the developed world. Furthermore, even when corrected, myopia can lead to severe secondary pathologies: Especially – though not exclusively – high myopia is associated with increased risk of conditions such as cataract, glaucoma and retinal detachment, and can even result in blindness (Rose et al., 2001; Saw et al., 2005). Logan and Wolffsohn (2020) reviewed the association between un-, under- and overcorrection of myopia and myopia progression in children and adolescents and – among other things – conclude that undercorrection causes faster myopic progression than full correction and that current clinical recommendation advocates for full correction of myopia. As secondary pathologies are mostly associated with high myopia (Rose et al., 2001), diagnosing and (fully) correcting myopia is thus not only helpful in preventing visual impairment from uncorrected myopia, but may also be an important step in minimizing the occurrence of secondary pathologies.

Myopia also constitutes a substantial, long-term economic burden for both the affected individuals and the public. This includes direct costs such as those for treatment as well as more indirect ones, for example due to the management of secondary pathologies or lost productivity (Flitcroft, 2012; Holden et al., 2014; Sankaridurg et al., 2021). The economic impact of myopia is particularly pronounced when left uncorrected: According to Naidoo et al. (2019), the global potential productivity loss resulting from vision impairment and blindness attributable to uncorrected myopia is estimated at US$244 billion. This figure substantially exceeds the costs associated with correcting myopia (Naidoo et al., 2019), emphasizing the importance of diagnosing and correcting myopia from an economic, public health standpoint.

Furthermore, both visual acuity and refractive errors can negatively affect educational outcomes (for a review, see: Hopkins et al., 2020), and corrective measures have the potential to mitigate this impact. For example, in an underserved area in rural China, early provision of free glasses to eligible children improved their academic performance in a mathematics test (Y. Ma et al., 2018). In low-income minority communities in the USA, parents, teachers, and students reported both the negative impact of uncorrected poor vision and how receiving free corrective lenses improved, among others, students' academic performance (Dudovitz et al., 2016). With regard to myopia specifically, Sankaridurg et al. (2021) state that despite the increasing popularity of digital technologies in the classroom, board work is still very common, imposing a barrier to learning for children with uncorrected myopia. In accordance,

upon providing free glasses to Chinese school children who had failed visual acuity screenings, X. Ma et al. (2014) found improvements in their mathematics test scores. The effect size of this analysis increased with increasing blackboard use, suggesting that children with myopia – compared to those with other refractive errors – had especially benefited from the glasses (X. Ma et al., 2014). In the USA, providing spectacles to disadvantaged children improved their reading performance – interestingly, the effects were greater for myopic than hyperopic children (Slavin et al., 2018).

Myopia can also affect a person's quality of life, for example with regard to activity limitation as well as economic, emotional, and social well-being. The impact on quality of life is especially severe in high myopia as well as uncorrected myopia. Myopia correction may not necessarily improve the quality of life to the point that it reaches emmetropic levels, as individuals with corrected myopia might e.g. be concerned about their appearance or potential correction-related complications. Yet, appropriate myopia correction has been shown to improve quality of life (Sankaridurg et al., 2021).

As has been demonstrated, myopia can potentially entail a range of negative consequences, both immediate and long-term. Meanwhile, myopia correction has the capacity to mitigate the impact of many of these potential consequences, thus underlining the importance of ensuring adequate diagnostics and correction of myopia.

1.1.4. Myopia Correction and Control

As described before, myopic individuals experience blurry distance vision because rays of light from distant objects are focused in front of the retina, which cannot be adjusted for via accommodation (Morgan et al., 2012). Generally, full correction of this myopic refractive error is clinically recommended (Logan & Wolffsohn, 2020; World Health Organization, 2016). For optical correction, concave lenses are used to move the focal point of distant objects back and onto the retina. This is most commonly done via spectacles. Contact lenses are also used, though they are not recommended for children. Furthermore, it is also possible to correct myopia via refractive surgery, whereby the corneal surface is flattened to reduce its optical power. However, this is generally recommended only after the stabilization of the refractive development – i.e., in the twenties (Morgan et al., 2012). To reiterate, the costs for correcting have been estimated to be substantially lower than the potential lost productivity associated with uncorrected myopia (Naidoo et al., 2019).

Apart from simply correcting for the myopic refractive error, there are also treatment options available that attempt to slow myopia progression, referred to as myopia control (interventions; Morgan et al., 2018). While undercorrection of myopia is not recommended for myopia control (Logan & Wolffsohn, 2020; World Health Organization, 2016), other

options are better supported, such as the application of atropine, orthokeratology (i.e., the wear of rigid, gas-permeable contact lenses during sleep to reshape the cornea), multifocal spectacles or soft contact lenses, and executive bifocal lenses (Brennan et al., 2021; Morgan et al., 2018; Spillmann, 2020; World Health Organization, 2016). However, evidence for the effectiveness of myopia control strategies varies (Morgan et al., 2018; World Health Organization, 2016) and aspects like rebound (i.e., accelerated myopia progression after treatment removal) and long-term safety still need to be studied more (Brennan et al., 2021; Spillmann, 2020). Behavioral and lifestyle changes that might also be regarded as myopia control interventions will be discussed in chapter 1.2. A review of myopia control strategies to slow myopia progression regarding their risks and benefits concluded that their potential benefits outweigh their risks (Bullimore et al., 2021). Overall, myopia control is a promising avenue for limiting the severity of myopia, thus reducing the impact of myopia and especially high myopia on affected individuals and the public.

To better understand the impact of myopia and high myopia on society, it is important to consider the prevalence of myopia and its development over time.

1.1.5. Myopia Prevalence

Myopia is one of the most common diseases of the eye worldwide (Foster & Jiang, 2014). Together with its diverse (potential) negative impacts – medical, financial, and otherwise –, this makes myopia a major public health issue. Furthermore, epidemiological studies show a prevalence increase over the last decades, particularly in younger cohorts (Holden et al., 2016; K. M. Williams, Bertelsen, et al., 2015), and in developed countries of (South)East Asia (Foster & Jiang, 2014; Morgan et al., 2012). In fact, this so-called "myopia boom" (Dolgin, 2015, p. 1) occurring over the last 60 years in (South)East Asia is generally considered an epidemic (Morgan et al., 2021; Spillmann, 2020), with up to 90% of adolescents and young adults being myopic (and 10-20% even highly myopic) today, particularly in urban areas (Dolgin, 2015; Morgan et al., 2012). This drastic development has taken place within a very short time span: While two or three generations ago, 20-30% of young adults who had completed 12-13 years of schooling were myopic, this number is now up to 70-90% (Morgan et al., 2021). In comparison, for many developed Western countries, 20-40% of adolescents and young adults finishing secondary schooling are estimated to be myopic (Morgan et al., 2018). High prevalence rates of myopia are not only reported for those finishing secondary schooling in (South)East Asia, but also for children. For example, a systematic review and meta-analysis reports a myopia prevalence of 46.2% for children and adolescents in China in studies published after 2015 – compared to 25.7% in studies published prior 2001 (Dong et al., 2020). Considerations regarding the factors driving this development will be thoroughly discussed in chapter 1.1.6.

While the situation is not nearly as grave in other parts of the world, a general increase of myopia prevalence has still been noted over the past decades. Summarizing data from 2000 to 2019 and from various regions all over the world, Sankaridurg et al. (2021) observed that while there is variation in prevalence across countries and regions, myopia is in fact rising in both children and adults. In estimating temporal trends in myopia and high myopia prevalence, Holden et al. (2016) also report a global increase of myopia from 22.9% in 2000 to 28.3% in 2010 and predict 50% of the world's population to be myopic by 2050, if not for myopia control interventions.

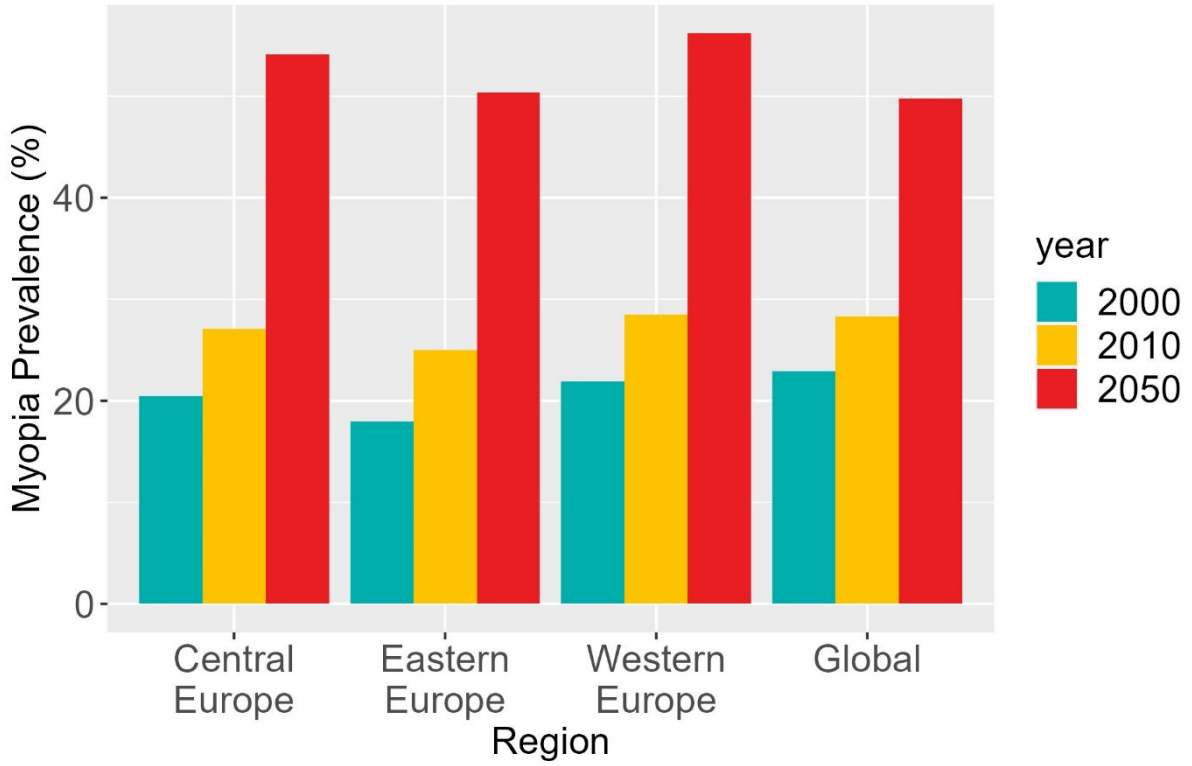

Figure 1.2. Global and European prevalence of myopia estimated by Holden et al. (2016). Regions are defined as Global Burden of Disease Regions. The estimations for the years 2000 and 2010 are based on past data, those of the year 2050 are projected prevalence rates. Data taken from Holden et al. (2016).

For Europe and across all age groups, Holden et al. (2016) report a rise in myopia prevalence between 2000 and 2010 as well, and predict a further increase to > 50% in 2050 (see Figure 1.2). Other investigations have also shown increases in myopia prevalence in Europe. For example, a meta-analysis on European data found higher myopia prevalence rates in younger than older birth cohorts in adult participants (born 1910-1979) across all age groups (K. M. Williams, Bertelsen, et al., 2015) and myopia prevalence slightly increased from 2.8% (6-7-year-olds) and 17.7% (12-13-year-olds) between 2006 and 2008 (O'Donoghue et al.,

2010) to 3.3% (6-7-year-olds) and 19.9% (12-13-year-olds) between 2016 and 2018 (Harrington, Stack, Saunders, & O'Dwyer, 2019) in Northern Ireland. Figure 1.3 presents recent European myopia prevalence estimations for children and adolescents. As can easily be seen, the European prevalence rates are both much lower than those in (South)East Asia and subject to rather high variation. As myopia prevalence can be assessed in various ways (see chapter 1.1.5.1), the latter may partly originate from methodological differences in prevalence estimation.

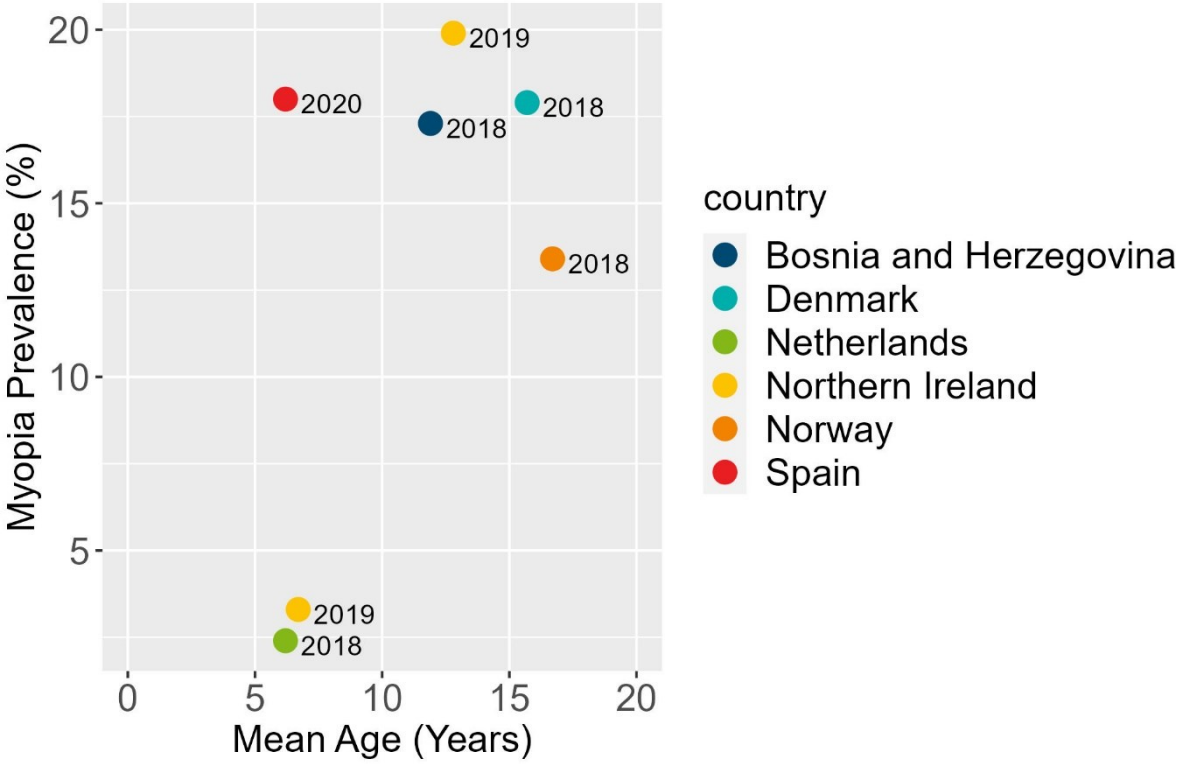

Figure 1.3. European myopia prevalence rates for children and adolescents. The annotated year represents the respective year of publication. Data taken from Popović-Beganović et al. (2018; Bosnia and Herzegovina), Lundberg et al. (2018; Denmark), Tideman et al. (2018; Netherlands), Harrington, Stack, Saunders, and O'Dwyer (2019; Northern Ireland), Hagen et al. (2018; Norway) and Alvarez-Peregrina et al. (2020; Spain). The mean age for Popović-Beganović et al. (2018) is taken from Xiang and Zou (2020). The mean age for Tideman et al. (2018) was calculated from separate data for myopic and non-myopic children in the sample.

A recent investigation presents myopia prevalence rates for children and adolescents in Germany, ranging from 2.1% in 3-year-olds to 25.9% in 17-year-olds (Truckenbrod et al., 2021). With regard to prevalence development in Germany, evidence from analyzing refractive values from opticians' accounting data (Wesemann, 2017) and questionnaire data (Schuster et al., 2020) suggests that myopia prevalence did not increase – but rather remained relatively stable – for 5-30-year-olds between 2000 and 2015 (Wesemann, 2017) and for 0-17-year-olds between 2003-2006 and 2014-2017 (Schuster et al., 2020), respectively. However, for both investigations, there has been some discussion about the validity of inferring the respective conclusions regarding myopia prevalence development (Barry, 2021; Finger & Schuster, 2019; Schuster, 2021; Wesemann, 2018, 2019; Ziemssen, 2018). What complicates the analysis of time trends in myopia prevalence is the frequent lack of current prevalence data, especially data from direct measurements of refractive status. Yet, up-to-date information on myopia prevalence and associations are important to reliably monitor prevalence development and to develop and adapt public health strategies for prevention and intervention. This frequent lack of current data includes prevalence rates of uncorrected myopia, which, as has been outlined in chapter 1.1.3, is also very relevant from a public health standpoint.

1.1.5.1. Assessment of Myopia Prevalence

Myopia prevalence can be assessed in various ways, and the respective methodology should be considered in data interpretation. In principle, myopia prevalence can be estimated either via direct measurements of refractive status or by more indirect means, for both of which there are again various methods.

There are a number of ways to indirectly estimate myopia prevalence rates. One recently used method, for example, is estimating prevalence rates via databases registering spectacle purchases (Wesemann, 2017) – a strategy which has subsequently been discussed with regard to aspects like sample representativeness (Finger & Schuster, 2019; Wesemann, 2018, 2019; Ziemssen, 2018). Another possibility to indirectly estimate myopia prevalence rates is using participant reports, for example from interviews or questionnaires, which may also be conducted online.

Direct measurements of refractive status can be divided into subjective and objective refraction. During subjective refraction, the participant is instructed to assess various lenses while focusing on a specific target, indicating which lens provides the clearest view of the target. Therefore, subjective refraction requires good communication and participant cooperation (Rosenfield, 2009). Subjective refraction encompasses different steps and techniques to identify the correction enabling the best visual acuity (Kaur & Gurnani, 2024),

but as it is not a topic of this dissertation, they will not be reflected upon further at this point. In practice, subjective refraction is routinely used to determine the best lens prescription for patients with refractive errors (Rosenfield, 2009). While identifying the refractive correction that enables a patient's best (subjective) vision is a key objective in clinical practice, researchers conducting epidemiological studies are usually primarily concerned with determining the actual status of participants' eyes – thus, they often use objective rather than subjective refraction. Objective refraction requires less participant involvement and does not rely on their feedback (Atchison, 2009). There are different objective refraction methods, including retinoscopy and autorefraction. In retinoscopy, the examiner uses an optical instrument – a retinoscope – to shine light into the participant's eye and to observe the movement of the light reflected within the participant's retina to determine their refractive error (Atchison, 2009; Enaholo et al., 2024; Hollis et al., 2022; Rosenfield, 2009). While retinoscopy often remains the method of choice for objective refraction, especially with young children, the procedure is time-consuming and potentially prone to examiner bias (Z. Liu et al., 2021). Autorefraction, on the other hand, is less dependent on examiner judgement as autorefractometers (or autorefractors) measure a person's refractive status automatically. The principle of autorefraction will be described in more detail in chapter 1.1.5.1.1.

Objective refractive measurements can be conducted with or without cycloplegia – i.e., the elimination of accommodation through administering cycloplegic agents. Most commonly, the muscarinic antagonists atropine, cyclopentolate and tropicamide are used (Baird et al., 2020; Duran & Cevher, 2023). These agents paralyze the ciliary muscle of the eye, which is essential in controlling accommodation (Baird et al., 2020). Accommodation can distort refractive measurements, overestimating the degree of myopia (Baird et al., 2020). This is prevented by the use of cycloplegia. It has repeatedly been shown that non-cycloplegic refractive measurements lead to more myopic refraction results than cycloplegic measurements (Flitcroft et al., 2019), especially in younger participants and hyperopic eyes (Fotedar et al., 2007; Grzybowski et al., 2020; Krantz et al., 2010; Rudnicka et al., 2016; Sanfilippo et al., 2014). Thus, the use of cycloplegia allows for more precise measurements of refractive status, especially in young children. However, the procedure is also more invasive and resource-intensive than non-cycloplegic measurements, and thus not necessarily always appropriate.

As described in chapter 1.1.2, -0.5D SER is usually used as a threshold for myopia classification. When conducting non-cycloplegic refractive measurements, one may counteract myopia overestimation by choosing a more conservative threshold (Flitcroft et al., 2019), and respective investigations have e.g. repeatedly used -0.75D SER instead (e.g., Alsaif et al., 2019; Truckenbrod et al., 2021; Yotsukura et al., 2020).

Overall, while the assessment of myopia prevalence rates itself is of course very important, it is also of relevance to investigate the methods with which this is done. There already is a certain amount of data on some methods – for example, performing objective refractive measurements with or without cycloplegia (Fotedar et al., 2007; Sanfilippo et al., 2014). Others, such as the usage of online questionnaires in the study of myopia epidemiology, are less investigated. Therefore, apart from generating myopia prevalence rates for school students via autorefraction, this dissertation also focuses on assessing online questionnaires as a means to investigate myopia prevalence (development). In the following, I will expand the description of the methodologies utilized for the assessment of myopia prevalence (development) in this dissertation: autorefraction and online questionnaires.

1.1.5.1.1. Autorefraction

Autorefraction is a method of objective refraction, in which the refractive status of the examined person is automatically measured. Typically, autorefraction involves the use of infrared (IR) radiation: The autorefractometer projects IR radiation into the eye and determines the refractive status by assessing the IR radiation that is reflected back from the eye (Campbell et al., 2006). IR radiation is electromagnetic radiation with wavelengths between 780 nm and 1 mm (International Commission on Illumination, n.d.–c). These wavelengths are longer than those of visible light and IR radiation can therefore not be perceived by the human eye.

As previously mentioned, autorefraction can be performed with or without cycloplegia. It is also typically a non-contact method in which the participant's refraction is measured from some distance (see Figure 1.4). Thus, in case of non-cycloplegic measurements, autorefraction is a non-invasive, fast and convenient procedure to objectively measure refractive status.

Figure 1.4. Autorefraction measurement with one of the autorefractometers used in this dissertation. (Plusoptix A12R; Plusoptix GmbH, Nürnberg, Germany).

1.1.5.1.2. Online Questionnaires

Online questionnaires allow for quick and easy acquisition of a lot of data, which is – in principle – useful for epidemiological studies. They may present a promising opportunity not only in terms of participant numbers, but also accessibility: Online recruitment has been shown to enable reaching a more diverse and representative sample than traditional recruitment (Gosling et al., 2004; Gosling et al., 2010; Upadhyay & Lipkovich, 2020). However, as the population to which an online questionnaire is distributed can often not be identified and may contain biases (Andrade, 2020), it is unclear to what extent obtained data are representative of the targeted population – which is problematic, especially for epidemiological investigations.

Aspects such as recommendations for frequency and content of ophthalmic examinations as well as refractive corrections differ between healthcare systems and countries. It is therefore important to make methodological considerations against the respective background – in case of this dissertation, this refers to myopia prevalence data from Germany. There has already been some research estimating myopia prevalence rates in Germany from questionnaire data with varying approaches. Jobke et al. (2008), for example, not only asked participants about specifications regarding refractive correction, but even

rechecked them with the respective opticians. Schuster et al. (2020) report data from the German Health Interview and Examination Survey for Children and Adolescents (KiGGS) – thus, the respective questionnaire did not only focus on refractive error or even eye health, but was more extensive. Yet, the precision of myopia-related estimates gained from questionnaire data remains unclear. This can be clarified by comparing myopia prevalence estimates from questionnaires and refractive measurements, which will be one focus of this dissertation.

1.1.6. Myopia Etiology

Beyond monitoring myopia prevalence rates and their development, it is also crucial to investigate the underlying causes for the respective development, and to use the results for the design of preventive and interventive measures. For example, consideration of myopia etiology is useful in explaining the prevalence development in the last decades. Furthermore, it underlines the necessity of monitoring myopia prevalence development especially in children and adolescents.

In general, myopia has a multicausal etiology. Genetic involvement in myopia has repeatedly been shown (Tedja et al., 2019). For example, in populations of European ancestry, genetic variation has been show to account for at least 12%, but probably even ≥ 30% of the variance in mean SER (Morgan et al., 2021). However, genetic factors cannot account for the rapid rise in myopia prevalence within the last decades, and it is assumed that the major risk factors of school myopia – the type of myopia that is responsible for said prevalence increase – are environmental in nature (Morgan et al., 2021; Tedja et al., 2019). Overall, myopia is assumed to be determined by a combination of genetic and environmental factors. The following sections will provide an overview of both genetic as well as environmental and lifestyle factors of myopia development.

1.1.6.1. Genetic Factors of Myopia

While genetic factors are most likely not the driving force behind the recent global increase in myopia (prevalence), they are undoubtedly involved in myopia development and may, for example, control myopia degree. Generally, estimates of myopia heritability vary greatly, ranging from 10% to 98% (Tedja et al., 2019). The degree of genetic disposition involved in the development of myopia seems to depend on the type of myopia: While school myopia is primarily environmentally determined, lenticular myopia (a type of refractive myopia with increased optical power of the lens) or specific rare forms of axial myopia are mostly caused by genetic disposition (Morgan et al., 2021; Spillmann, 2020).

The genetic component of myopia has been investigated in various ways, including linkage studies (aiming at identifying genetic markers cosegregating with myopia in families and high-risk groups), candidate gene studies (investigating specific genes based on their known potential relevance for myopia), and whole-exome sequencing studies (predominantly conducted in case-control studies of early-onset high myopia or families exhibiting a specific phenotype). In recent years, many genome-wide association studies (GWAS) have investigated both myopia and refractive error, thereby either using (high) myopia as a dichotomous outcome or refractive error as a quantitative trait, or considering endophenotypes such as axial length (Muralidharan et al., 2021; Tedja et al., 2019). Overall, over 200 genetic loci have been identified for refractive error and myopia (Muralidharan et al., 2021), with risk variants being highly prevalent in the population, but predominantly having small effects each (Tedja et al., 2019). Furthermore, only a fraction of the phenotypic variance in refractive error can be explained via genetics to date. For example, a large GWAS meta-analysis identified 161 common variants for refractive error, but they only accounted for 7.8% of said phenotypic variance (Tedja et al., 2019).

Of note, the large differences in myopia prevalence rates between ethnicities have often been cited as evidence for a genetic predisposition of myopia. However, the term ethnicity not only includes genetic factors – with differences between ethnicities being small in comparison to what human populations have in common genetically –, but also cultural factors. In fact, it seems that environmental factors, rather than genetic ones, underlie the myopia prevalence differences between ethnicities (Morgan et al., 2021). For example, Rose, Morgan, Smith, et al. (2008) found that 6-7-year-old students of Chinese ethnicity in Sydney had a much lower myopia prevalence (3.3%) than age- and ethnicity-matched students in Singapore (29.1%), with the difference inversely correlating with average time spent outdoors (see chapter 1.1.6.2), suggesting a predominantly environmental influence. Furthermore, the aforementioned GWAS meta-analysis suggests a rather similar genetic architecture of refractive error for European and Asian individuals – and overall, there currently is no robust evidence supporting fundamental differences in the genetic background of myopia risk between said groups (Tedja et al., 2019).

Thus, while genetic factors are clearly involved in myopia, their level of involvement varies with the type of myopia, and they do not underly the rapid prevalence increase over the last decades. Instead, this is most likely the cause of environmental and lifestyle influences.

1.1.6.2. Environmental and Lifestyle Factors of Myopia

Multiple environmental and lifestyle factors have been associated with myopia in the past, among which are family socioeconomic status, family income, pollution and health conditions during childhood (Foster & Jiang, 2014; Morgan et al., 2018; Rose et al., 2016; Spillmann, 2020). It has, however, been concluded that there is no clear evidence that any of these factors alone substantially increases the risk of myopia (Morgan et al., 2018; Rose et al., 2016). On the other hand, there is strong evidence for an association between myopia and multiple aspects of education, such as years of education, academic performance and attending selective schools (Rose et al., 2016). These findings entail the necessity to assess other reported risk factors, including the aforementioned ones, with regard to being potentially confounded with education (Morgan et al., 2018).

Education has often been associated with the rapid myopia prevalence increase in certain world regions in the last decades. It has also been hypothesized that differing educational pressures and developments between education systems (partly) explain the difference in myopia prevalence development between world regions. Historically, high rates of myopia prevalence have been reported in academic environments and people with higher education as early as the 19th century (for a review, see: Spillmann, 2020): For example, in 1813, Ware published his inquiries about myopia in individuals in "different ranks of society" (Ware, 1813, p. 32), reporting that within three regiments of foot guards (almost 10,000 men), less than six had been discharged and less than six recruits rejected due to myopia over almost 20 years. Furthermore, among 13,000 children at the military school in Chelsea, only three had experienced any myopia-related inconvenience. At the same time, there was a high prevalence of myopia in colleges at Oxford and Cambridge – with 32 out of 127 students at one college at Oxford using either hand glasses or spectacles (Ware, 1813). Other investigations from the same and the following century also found increased prevalence of myopia with increasing school grades and length of education (Spillmann, 2020).

The impact of education on the development of myopia has repeatedly been shown more recently as well: Myopia prevalence rates are generally low in societies with little formal education (Morgan et al., 2018; Rose et al., 2016). For example, low myopia prevalence rates have been found for school students aged 12 (5.5%), 13 (6.0%) and 14 (6.0%) years in Cambodia (Gao et al., 2012), a Southeast Asian country with comparably little formal education, indicating that myopia prevalence rates remain low in children and adolescents with little exposure to education (Morgan et al., 2018). Another interesting example are the Inuit, who had exhibited very low myopia prevalence rates, which then rapidly increased around the 1970s – coinciding with the introduction of formal education in the respective settlements (Morgan et al., 2018; Spillmann, 2020).

Increases in myopia prevalence rates also coincided with educational changes on a larger scale. In Europe and North America, myopia prevalence increases can be traced back to the early 20th century, when modern education systems were introduced (Morgan et al., 2018). European data for example shows considerably increased myopia prevalence rates across age groups for adults born 1940 and after compared to earlier birth cohorts (K. M. Williams, Bertelsen, et al., 2015). Furthermore, for Germany, Wesemann (2018) reanalyzed data from the "Allensbach Brillenstudie" ("Allensbach spectacle study") and reports that the number of spectacle-wearing young adults almost tripled between 1952 and 1983. He points out that this development coincided with the educational campaign of the 1960s and 1970s, which aimed at providing more children from non-academic backgrounds with university education (Wesemann, 2018).

The current "myopia boom" in countries of (South)East Asia is likewise attributed to educational changes, as the rapid increase in myopia prevalence emerged with the introduction of highly competitive mass educational systems – which happened after the introduction of modern educational systems in Western societies (Morgan et al., 2018; Rose et al., 2016; Spillmann, 2020). Myopia prevalence rates suddenly increased in Hong Kong, Taiwan, Singapore, and South Korea between 1962 and 1969 (Spillmann, 2020) and continued to rise after that. For example, from 1983 to 2000 in Taiwan, the prevalence of myopia increased from 5.8% to 21% for 7-year-olds, and from 74% to 84% for 16-18-year-olds (L. L. K. Lin et al., 2004). In China, a rapid increase of myopia prevalence rates occurred following the Cultural Revolution in the 1970s and the reintroduction of the gaokao, the competitive university entrance examination (Morgan et al., 2021; Spillmann, 2020). To date, 46.2% of 3-19-year-olds in China are myopic (Dong et al., 2020). Overall, 70-90% of young adults who completed 12 to 13 years of schooling are myopic in (South)East Asia (Morgan et al., 2021) – with myopia prevalence rates even sometimes surpassing 90%, e.g. in university students in China and Taiwan (Spillmann, 2020). Interestingly, similarly high myopia prevalence rates (82.2%) have been reported in Israel for Jewish male adolescents attending ultra-Orthodox schools (Bez et al., 2019), again strongly suggesting the influence of educational pressures – instead of factors such as ethnicity – on myopia development.

In fact, genetic research also supports a causal link between education and myopia, namely via Mendelian randomization (MR). In MR, the association between so-called instrumental variables – genetic variants that are associated with the exposure of interest – and an outcome of interest is tested (Tedja et al., 2019). Simply put, MR studies showed that individuals with a genetic "predisposition" to higher education – operationalized by using results of a large GWAS on educational attainment – were more prone to being myopic (Cuellar-Partida et al., 2016; Mountjoy et al., 2018). Conversely, MR analyses provided little evidence to suggest that genetic predisposition to myopia had a causal effect on the amount of time spent in education (Mountjoy et al., 2018). Furthermore, Mirshahi et al. (2014) showed

that education had a considerable effect on SER, while genetic effects – operationalized as myopia-associated SNPs (single nucleotide polymorphisms) – were also present, but weak.

Rose et al. (2016) state that while generally only countries with high educational performance are known to have a high myopia prevalence, some countries with high educational performance – e.g., New Zealand and Australia – do not exhibit a myopia epidemic. Thus, considering factors that (may) underlie the undeniable association between myopia and education is important to identify preventive measures that could enable low myopia prevalence rates despite high educational performance. Already in the 19th century, Cohn (1886) suggested measures such as increasing reading distance and ensuring good lighting conditions in classrooms to counteract myopia. In fact, the amount of *near work* – activities with a short working distance, such as reading, writing, drawing and using handheld electronic devices – and (bright) *light exposure* are two important lifestyle factors implicated in myopia. They are also hypothesized to mediate the impact of education, with near work believed to be a risk factor and (bright) light exposure considered protective (Rose et al., 2016). These factors are still heavily researched today and their involvement in myopia development also explains the finding of increased myopic progression among children and adolescents during the Covid-19 pandemic: Related measures such as online schooling most likely increased their time spent on near work and decreased their outdoor activities in bright light (for a meta-analysis, see: Watcharapalakorn et al., 2022). Although a connection could be assumed between the influence of near work and (bright) light exposure on myopia – e.g., outdoor activities simply replacing near work time (Rose et al., 2016) –, they have been identified as independently associated factors (Rose et al., 2016; Rose, Morgan, Ip, et al., 2008; Wen et al., 2020).

There is no universally accepted definition for near work (Wen et al., 2021), and various quantifications and surrogate measures are used to assess it (R. Williams et al., 2019). In terms of viewing distance, near work has often been defined as activities in < 50 cm, but lower thresholds such as < 40 cm and < 30 cm have also been used (Z. Lin et al., 2017; Rose, Morgan, Ip, et al., 2008; Wen et al., 2021). Associations between near work activities and myopia have been found repeatedly, but not consistently. Overall though, a systematic review and meta-analysis showed that despite substantial methodological differences between investigations, more time spent with near work activities was associated with higher odds of myopia (odds ratio = 1.14) – thus making near work a risk factor for myopia. Several hypotheses have been and are being discussed as potentially underlying the detrimental effect of near work on myopia. According to Rose et al. (2016), effects of hyperopic defocus resulting from accommodative lag during prolonged near work constitute the most plausible explanation for said association.

Exposure to bright/outdoor light, on the other hand, has repeatedly been found to protect against myopia (for reviews, see: Eppenberger & Sturm, 2020; Ho et al., 2019), and associations between time spent outdoors and myopia are generally stronger and more consistent than those between near work and myopia (Morgan et al., 2021). It is even suggested that time spent outdoors can minimize or eliminate the influence of other factors associated with myopia, including near work (French et al., 2013). The association between (bright) light exposure and myopia will be discussed in-depth in the following.

1.2. Light and Myopia

Prior to uncovering the association between light exposure and myopia, it became apparent that time spent outdoors was protective against myopia. Though a respective relationship had long been suspected, serious scientific evidence of time outdoors being a protective factor against myopia was not presented until 1993 (Rose et al., 2016) – when a longitudinal study showed that in boys (but not girls), more time spent outdoors was associated with less myopia progression and a lower degree of myopia (Pärssinen & Lyyra, 1993). Since then, time spent outdoors has repeatedly emerged as a protective factor with predictive value for myopia in children (for a review, see: French et al., 2013). Findings such as more outdoor/sports activities being associated with reduced odds of myopia (Jones et al., 2007) and myopic children spending less time with sports activities than non-myopic children (Mutti et al., 2002) then raised the question whether the actual protective factor was being outdoors or being physically active (Rose et al., 2016). Further research has since shown that outdoor activities (both leisure and sports) protect against myopia, whereas indoor sports activities do not (Dirani et al., 2009; Rose, Morgan, Ip, et al., 2008; for a review, see: Rose et al., 2016). This has also been confirmed by Guggenheim et al. (2012), who discovered an association between accelerometer-measured physical activity and myopia, but an even greater association between time outdoors and myopia, with time outdoors being predictive of myopia independent of physical activity. More recently, the association between outdoor time and myopia has been investigated by categorizing a participant's location as indoors or outdoors via light intensity measurements from wearable light meters. While investigations using this methodology will be expanded upon later (see chapter 1.2.3), it is worth noting here that several of them report associations between myopia and reduced outdoor time (e.g., Bhandari et al., 2022; Wu et al., 2018). Furthermore, myopia progression rates differ between seasons, with faster progression in winter than summer, which is consistent with a protective effect of time outdoors, but also with near work as a risk factor due to reduced study time during summer (holidays; French et al., 2013; Morgan et al., 2018; Rose et al., 2016).

In the last decade, intervention studies have shown that promoting and increasing children's outdoor time are effective in reducing myopia (M. He et al., 2015; X. He et al., 2022; Wu et al., 2013; Wu et al., 2018), again producing strong evidence for outdoor exposure as a protective factor against myopia. Specifically, Wu et al. (2013) report that after participating in a program promoting outdoor activities during recess in 7-11-year-old school children in Taiwan, there was lower myopia onset and myopic shift in the intervention than control group after 1 year. However, the intervention was only a protective factor regarding myopic shift in non-myopic, but not myopic, children (Wu et al., 2013). Some years later, Wu et al. (2018) investigated a program in which 6-7-year-old school children in Taiwan were encouraged to go outside for 11 hours per week. Upon completion of the 1-year-trial, the intervention group showed less myopic shift and axial elongation as well as lower incidence of myopia onset and rapid myopia progression than the control group. Here, protective effects were present both in myopic and non-myopic children (Wu et al., 2018). In China, an additional 40 minutes of outdoor activities per school day as well as out-of-school outdoor activities were encouraged for 6-year-old primary school children over a 3-year-trial (M. He et al., 2015). Results showed a reduced myopia incidence rate and SER change in the intervention compared to the control group, but no significant difference in axial length change over 3 years (M. He et al., 2015). In another program by X. He et al. (2022), additional 40 or 80 minutes of outdoor time per school day over 2 years were allocated for 6-9-year-olds in two different intervention groups in China. After 2 years, the authors found a reduced myopia incidence rate as well as less myopic shift and axial elongation in both intervention groups compared to the control group. Protective effects of outdoor time (measured with a wearable device) on myopic shift in both SER and axial length were also observed, but only in non-myopic participants. Furthermore, there was no significant difference in myopia incidence or shift between the intervention groups, but they also exhibited similar outdoor time and light intensity (X. He et al., 2022). Impressively, recent Taiwanese data show that following the implementation of a program aiming at 2 hours of daily outdoor time for primary school children as a governmental policy in 2010, prevalence rates of reduced visual acuity in primary school children have started to decline. This marks a reversal in the previous trend of rising prevalence of reduced visual acuity associated with the myopia boom in school children in Taiwan (Wu et al., 2020).

These data demonstrate the potential of promoting outdoor activities as a strategy for myopia prevention and possibly also as a myopia control intervention. The effect of outdoor exposure on myopia progression is generally less clear than on myopia onset. For example, a meta-analysis on outdoor exposure and myopia – with most included studies assessing the former via questionnaires – concluded that while increase time outdoors can effectively prevent myopia onset and slow myopic shift in refractive error, it is not effective in slowing progression in already myopic eyes (Xiong et al., 2017). Outdoor activities may thus

be more suited as myopia prevention than control interventions. However, protective effects of outdoor exposure on myopia progression have sometimes been reported before (Wu et al., 2018), and the seasonal differences in myopia progression that have repeatedly been observed suggest that myopia progression can indeed be regulated by environmental factors (Morgan et al., 2021). Rose et al. (2016) propose that the absence of an effect of time outdoors on myopia progression may be a statistical problem due to the narrower range of (near work and) time outdoors in myopic persons compared to the general population. More research will hopefully clarify if, or under which circumstances, outdoor exposure is also effective with regard to reducing myopia progression.

Various hypotheses have been proposed to explain the association between outdoor time and myopia, and it is of course possible that several of them are (partly) correct. It has, for example, been suggested that reduced peripheral defocus in outdoor versus indoor environments or the spatial frequency characteristics of outdoor environments are of relevance, though more research is needed to (further) substantiate either idea (Lingham et al., 2020). Several hypotheses involve properties of light as crucial factors, and will thus be expanded upon in chapter 1.2.2. Of these, the idea of the higher illuminance in outdoor versus indoor environments being crucial with regard to myopia protection is very well supported and has been described as the most established theory regarding the association between myopia and time outdoors (Lingham et al., 2020). Therefore, it is important to specify the definition of (bright) light and associated parameters. Prior to discussing the association between light and myopia in more detail, I will thus present a brief overview of the relevant physical properties of light.

1.2.1. Physical Properties of Light

Light, or visible light, is defined as the range of electromagnetic radiation that is visible to humans (International Commission on Illumination, n.d.–a; Sliney, 2016).[1] While there are no precise limits for the visible spectrum, electromagnetic radiation with wavelengths of 360-400 nm and 760-830 nm usually constitutes its lower and upper limits, respectively (International Commission on Illumination, n.d.–b). Different wavelengths within the visible spectrum are perceived as different colors, with, for example, short wavelengths being perceived blue, medium wavelengths green, and longer wavelengths red. Shorter wavelengths adjacent to the visible spectrum (100-400 nm) constitute ultraviolet (UV) radiation (International Commission on Illumination, n.d.–d). They are also referred to

[1] The definition given by the International Commission on Illumination (CIE) specifies that the term "light" has two meanings which should be clearly distinguished. The other one, which the International Commission on Illumination (n.d.–a) recommends to refer to as "perceived light" to avoid confusion, defines light as the characteristic of all vision-specific sensations and perceptions.

as UV light, even though they cannot be perceived by the human eye – though as stated by the CIE, visible sensation at wavelengths that are shorter than 400 nm has been detected for very bright light sources, so a precise boundary to visible light cannot be defined (International Commission on Illumination, n.d.–d). On the other hand, longer wavelengths adjacent to the visible spectrum (780 nm – 1 mm) constitute infrared (IR) radiation (International Commission on Illumination, n.d.–c). IR radiation is also referred to as IR light, and, as mentioned earlier, is for example utilized in autorefraction (see chapter 1.1.5.1.1). Again, a precise boundary to visible radiation cannot be set since visible sensation can occur even at wavelengths longer than 780 nm (International Commission on Illumination, n.d.–c). While the radiation spectra of artificial light sources lie circa within the visible – and in case of incandescent lamps also largely within the IR – spectrum, that of the sun includes both UV and IR light in addition to visible light (Cosic et al., 2016; L. Wang & Yu, 2023).

The human eye is not equally sensitive to all wavelengths on the visible spectrum. The photopic luminous efficiency function V(λ) describes the spectral sensitivity of human central vision for photopic vision – i.e., when it is bright and cones are the primarily active photoreceptors (International Commission on Illumination, n.d.–e, n.d.–i, n.d.–k). There are also other luminous efficiency functions. For example, the scotopic luminous efficiency function V′(λ) specifies the spectral sensitivity under low light conditions when rods are the primarily active photoreceptors (International Commission on Illumination, n.d.–e, n.d.–j, n.d.–l). Figure 1.5 depicts the photopic and scotopic luminous efficiency functions.

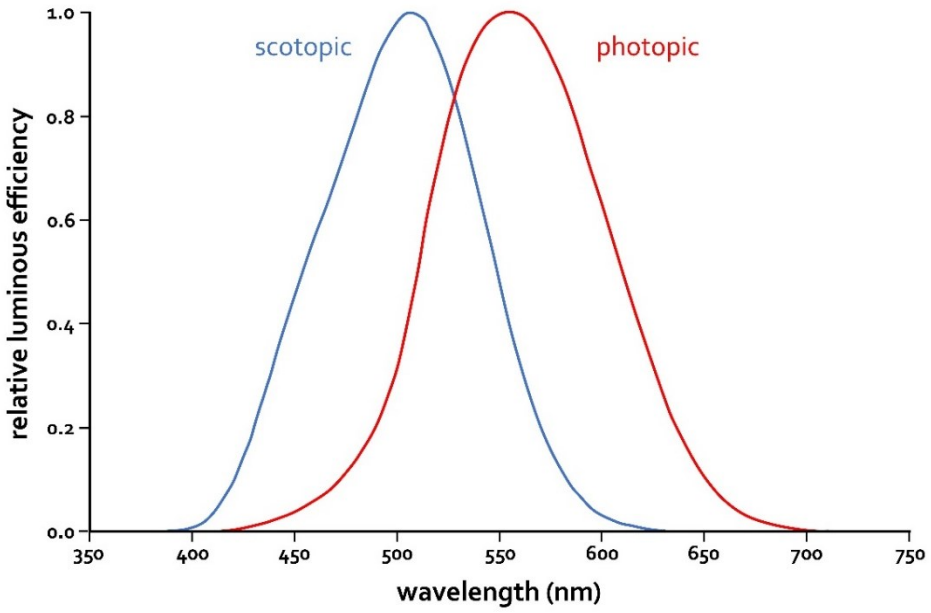

Figure 1.5. Photopic and scotopic luminous efficiency functions.

In this dissertation as well as commonly in the literature on the association between light and myopia, the term "light intensity measurements" refers to measuring lux. Lux is the measurement unit of illuminance, which is defined as spectral irradiance weighed by V(λ), unless it is specified to be based on another luminous efficiency function (Figueiro et al., 2013; Ohno et al., 2020). Spectral irradiance is defined as the density of irradiance per wavelength (International Commission on Illumination, n.d.–h), and irradiance is the density of radiant flux that is received by a surface per unit area (International Commission on Illumination, n.d.–g). Radiant flux, or radiant power, describes the change of radiant energy per unit time (International Commission on Illumination, n.d.–f). Importantly, despite this precise definition of lux, light meters may not always measure illuminance as accurately, because the spectral sensitivity of their sensor(s) may deviate from V(λ) (Figueiro et al., 2013; Joyce et al., 2020). This aspect should be kept in mind with regard to lux measurements via light meters as discussed throughout this dissertation.

1.2.2. Light-Myopia Associations and Potential Mechanisms of Action

In the following, reasons for the assumption that light exposure plays a causative role in myopia will be discussed in more detail. As outlined above, there are the findings of time spent outdoors being protective against myopia in humans, with (among others) light exposure being hypothesized as underlying this association. Furthermore, several studies with wearable light meters also report an association between exposure to bright light above various lux thresholds and reduced myopia (metrics; e.g., Read et al., 2015; Wen et al., 2020). As mentioned earlier, investigations using this methodology will be expanded upon at a later point (see chapter 1.2.3). Additionally, genetic research suggests that many of the genetic loci associated with myopia are functionally related to light processing and genome-wide pathway analyses have demonstrated that light processing is an important mechanism in refractive error development (Tedja et al., 2019). Research with experimentally induced myopia in animals also supports a protective effect of high light intensities regarding myopia development (e.g., Ashby et al., 2009; Karouta & Ashby, 2015; Smith et al., 2012). However, some studies do not find said association (e.g., Smith et al., 2013), and the type of induced myopia has been discussed to potentially play a role in this. In form-deprivation myopia, the eye is typically covered with a translucent diffuser to prevent clear vision, leading to abnormal elongation of the eyeball, while lens-induced myopia involves the placement of concave lenses in front of the eye to stimulate axial elongation. Thus, both types of experimentally induced myopia produce axial myopia (Morgan et al., 2013). Protective effects of bright light on myopia development have been more consistently found in form-deprivation than lens-induced myopia, and there has been some discussion with regard to the transferability of either model to human myopia (Rose et al., 2016). However, there also have been reports of

bright light being protective against lens-induced myopia (e.g., Biswas et al., 2023), and despite some inconsistencies and open questions, animal studies thoroughly demonstrate the presence of a light-myopia association.

This association is also underlined by evidence for possible mechanisms of action. In this regard, the light-dopamine hypothesis is very well-supported. Initially proposed by Rose, Morgan, Ip, et al. (2008), it states that bright light protects from myopia via light-stimulated release of retinal dopamine, which, in turn, inhibits eye growth. Dopamine is, in fact, an important regulator of eye growth (for a review, see: Stone et al., 2013), and retinal dopamine has been known to be regulated by light for some time now (Brainard & Morgan, 1987; Iuvone et al., 1978). Furthermore, in support of this hypothesis, animal studies have shown that dopamine agonists inhibit axial elongation and block myopia development in experimental myopia (McCarthy et al., 2007; Rohrer et al., 1993), and that the protective effect of light against myopia development can be blocked by a dopamine antagonist (Ashby & Schaeffel, 2010; McCarthy et al., 2007). Yet, as mentioned earlier, more than one hypothesis has been proposed regarding the protective effect of properties of light against myopia. For example, it has been postulated that exposure to UV light might be of relevance (Prepas, 2008). Vitamin D expression due to UV light exposure has also been proposed as a potential mechanism, as has the different chromatic spectrum of light outdoors versus indoors (with artificial indoor lighting being more monochromatic) and specifically violet light (360-400 nm) being of importance (for a review, see: Lingham et al., 2020). While there is some evidence for these hypotheses, they are generally not as well-supported as the light-dopamine hypothesis. For example, research has shown that the protective effect of bright light against myopia development in experimental myopia is present in the absence of UV light (Rose et al., 2016). Evidence for the involvement of vitamin D is inconsistent, and a causal relation with myopia seems unlikely (Lingham et al., 2020; Rose et al., 2016). Regarding the involvement of different chromatic spectra of light in myopia development, current evidence is still deemed relatively weak, with more investigations needed (Lingham et al., 2020). Overall, despite there still being some inconsistencies with the light-dopamine hypothesis, it currently is a very strongly supported theory explaining the protective effect of outdoor/bright light exposure against myopia. This does, however, not imply that other mechanisms do not also play a role in this association (Rose et al., 2016).

Overall, many of the proposed hypotheses regarding the protective effect of outdoor/bright light exposure against myopia are either deemed unlikely or in need of more research to substantiate them, while the light-dopamine hypothesis is a well-established and strongly supported theory. However, this does not necessarily mean that other mechanisms do not also play a role in this association. In any event, strong evidence suggests that (the amount of) light exposure plays a causative role in myopia development. This knowledge, in turn, may be used with regard to preventive and interventive measures to reduce onset and

progression of human myopia. In the following, I will extend the discussion on the investigation of light-myopia associations in humans to describe the methodologies used to generate and expand said knowledge.

1.2.3. Light-Myopia Association in Humans:Investigations Using Light Meters

As has been described before, questionnaires can be used to assess the amount of outdoor time. However, due to factors like their retrospective and subjective nature, these methodologies do not provide precise estimates. Furthermore, they are generally used to assess time spent indoors versus outdoors, but not in specific light intensities.

Thankfully, technological advancements have created new possibilities to assess both time outdoors and light exposure more objectively (for a review on measuring outdoor time in child myopia research, see: Jing Wang et al., 2018). For example, global positioning system (GPS) devices or conjunctival ultraviolet autofluorescence photography – a non-invasive procedure to detect UV light-related changes/damage of the ocular surface –, can be used. Yet again, these methods only allow for an estimation of indoor versus outdoor time, and not time in specific light intensities. In recent years, an increasing amount of research on the association between light and myopia has been conducted with wearable light meters that can measure a person's light exposure during their daily routine. Many wearable devices are available for the measurement of light exposure (for a review, see: Hartmeyer et al., 2022), and various light meters have already been used to investigate light-myopia associations. The devices in question measure lux, with some being able to also measure other light-related properties, such as UV light (e.g., Vivior Monitor, Vivior AG, Zurich, Switzerland) or red, green and blue light (e.g., Actiwatch Spectrum, Philips Respironics, Murrysville, PA, USA) as well as further aspects, for example activity (e.g., Actiwatch 2, Philips Respironics, Murrysville, PA, USA) or viewing distance (e.g., Clouclip, Hangzhou JingZhiJing Technology Co. Ltd.). As mentioned above, studies using wearable light meters often analyze the relation between myopia and time outdoors. Thereby, the latter is usually inferred from the time spent in light levels above a certain lux cut-off, typically 1,000 lux (e.g., Mirhajianmoghadam et al., 2021; Read et al., 2014; Wen et al., 2020).

While early studies utilizing light meters do not report associations between light/outdoor exposure and myopia (Alvarez & Wildsoet, 2013; Backhouse et al., 2011; Dharani et al., 2012; Schmid et al., 2013), subsequent research has repeatedly found such associations. For example, emmetropic children have been found to receive greater daily light and/or outdoor exposure than myopic children (Bhandari et al., 2022; Mirhajianmoghadam et al., 2021; Read et al., 2014) as well as more exposure to higher light intensities (Wen et al., 2020). Longitudinally, among others, greater light exposure was

associated with less axial elongation in children (Read et al., 2015) and reduction in myopia incidence was observed with increasing level of both outdoor time and outdoor light intensity (X. He et al., 2022). Even in the last few years, however, light-myopia associations have not been found in all investigations using light meters (e.g., M. Li et al., 2021; Ostrin et al., 2018), and multiple aspects are still unknown regarding light/outdoor exposure and myopia. For example, as has been discussed before (see chapter 1.2), it is not yet clear whether increased outdoor exposure can reduce only onset, or also progression of myopia (Morgan et al., 2021). Light meter studies may help in answering open questions such as this via objective measures of light (and outdoor) exposure.

These results demonstrate that various factors (may) play a role in the link between light exposure and myopia. Furthermore, the respective investigations differ a lot with regard to methodology, such as the specifications of the participant sample, time and location of data acquisition, and data analysis procedures as well as in the utilized light meters. This may also contribute to between-study differences in the results, and should therefore be considered in the research field.

1.2.4. Comparability of Different Light Meters

While light meters are increasingly used to assess light-myopia associations, methodological assessments and comparisons between different light meters are still rather sparse. This is problematic insofar as the utilized devices differ in many ways, for example how and where they are (supposed to be) worn or the included sensors and their technical specifications. Furthermore, several studies demonstrated differences in the measurements of different types of light meters and their deviations from photometer measurements (Figueiro et al., 2013; Howell et al., 2021; Joyce et al., 2020). The differences in between-device lux measurements and their (potential) relevance for studies on light-myopia associations is illustrated, for example, by the fact that 533.15 lux and 850 lux were identified as corresponding to photometer-measured 1,000 lux for Actiwatch 2 and Clouclip M2, respectively (Howell et al., 2021) – with 1,000 lux commonly being used as indoor-outdoor cut-off for various light meters, including these two devices (Read et al., 2014; Wen et al., 2020). Lux measurement differences have also been reported for similar devices worn at different locations on the body (Aarts et al., 2017; Figueiro et al., 2013; Wen et al., 2021) – and, unsurprisingly, also for different devices worn at different locations of the body (Read, Vincent, et al., 2018; van Duijnhoven et al., 2017). Yet, especially the latter is usually more of a side result of the respective investigations, with few studies systematically investigating such between-device differences or considering data from more than just one or a few hours.

Thus, little is known about how different types of light meters differ in their measurements in settings that closely resemble those in light-myopia field research. This would, however, be important knowledge with regard to the comparability of investigations that used different devices, which are often worn at different locations of the body. A recent dissertation reports data from 59 participants who had simultaneously worn three different light meters (Clouclip M2, Actiwatch 2, and HOBO Pendant UA-002-64, Onset Computer Corp., Bourne, MA, USA; Phan, 2022), showing poor correlations and significant differences between the devices' light intensity measurements. These results as well as the limited number of studies (systematically) investigating between-device differences underline the necessity of more methodological research to assess the comparability between light meters used in the study of light-myopia associations.

1.3. Research Objectives

The main body of this dissertation is structured around two primary aims. The first aim is to investigate myopia prevalence rates and associated factors in children and adolescents in Germany. The second aim is to examine methodological aspects of light-myopia research, with a primary focus on the utilization of light meters. Thereby, the above considerations accumulate in the three main research objectives of this dissertation, the first two of which will be investigated under the first aim (Part I), and the third one under the second aim (Part II):

Objective 1

Obtaining Current Myopia Prevalence Rates for Children and Adolescents in Germany

To address the existing gaps in myopia prevalence data, the first research objective centers on the acquisition of up-to-date myopia prevalence rates among children and adolescents in Germany. This includes the investigation of associations between both myopia and refractive status and sociodemographic factors like grade or gender as well as estimating the prevalence of uncorrected myopia.

In doing so, I utilized two different methodologies to assess myopia prevalence as described in chapter 1.1.5.1: Conducting non-cycloplegic autorefraction measurements in two student samples that constitute the lower and upper end of the age span in which school myopia usually appears (Study 1), and distributing an anonymous online parent questionnaire on spectacle ownership in children and adolescents in Germany (Study 2 and Study 3).

Objective 2

Assessing the Application of Online Questionnaires in Myopia Prevalence Research

The second research objective focuses on methodological considerations regarding the usage of online questionnaires in this type of epidemiological research. Specifically, I assessed the success of various recruitment strategies for online questionnaires as well as the feasibility of online questionnaires to investigate epidemiological matters such as myopia prevalence rates and associations.

The former was investigated by evaluating various aspects – e.g., sample representativeness and recruitment success – of the different recruitment strategies employed to distribute the aforementioned online questionnaire on spectacle ownership (Study 2). For the latter, I compared the online questionnaire data to the myopia prevalence rates acquired from the refractive measurements in Study 1 as well as other investigations (Study 3).

Objective 3

Extending Methodological Insights into the Usage of Light Meters in Myopia Research

With light meters being used more and more in investigations on light-myopia associations and as methodological aspects may influence their results, the third research objective aims to reduce the data gap with regard to light meter comparability as well as methodological aspects of the investigations in which they are being used. Furthermore, this objective also focuses the fact that commercially available light meters do not necessarily combine all features one might need for one's research.

To this end, I conducted a literature review on different light meters used in investigations on light exposure and myopia as well as the respective investigations' methodological parameters (Study 4). Furthermore, I employed various light meters that have been used in myopia research before in a real-life setting by wearing them simultaneously to directly compare their measurements (Study 5). Finally, wearable device prototypes were developed and assessed to explore the feasibility of developing a light meter tailored to the requirements of the specific situation of one's investigation (Study 6).

2. Part I

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Investigation of Myopia Prevalence and Associated Factors in Children and Adolescents in Germany: Epidemiological and Methodological Aspects

2.1. Study 1:

Myopia Prevalence, Refractive Status and Uncorrected Myopia Among Primary and Secondary School Students in Germany

Abstract: The increasing prevalence of myopia worldwide is problematic because myopia can result in severe secondary pathologies, and is associated with considerable financial burden. With plenty of prevalence data available for some regions, current data for Europe remain sparse. Yet, information on myopia prevalence and associations is essential for monitoring, preventive and interventive purposes. Likewise, uncorrected refractive errors are also critical, as they can e.g. affect educational outcomes, making information on uncorrected myopia valuable for diagnostics and health education. We performed non-cycloplegic autorefraction on two samples in Germany. The younger sample included 489 primary school students (grades 3-4, mean age: 9.30±0.78 years), the older sample 1032 secondary school students (grades 8-10, mean age 14.99±1.12 years). These samples mark the limits of the age range during which school myopia usually emerges. Myopia (spherical equivalent ≤ -0.75D) prevalence was 8.4% in the younger sample and 19.5% in the older sample. The prevalence was generally higher in higher grade levels, with the most notable difference between grades 8 and 9. Females were more myopic than males in all grades except grade 3, with the largest gender difference in grade 10. The older sample also exhibited a more myopic spherical equivalent than the younger sample. In the older sample, spherical equivalent was more myopic in females than in males, and in grade 9 and 10 participants more than in grade 8 participants. Rates of uncorrected myopia were extremely high: 51.2% in the younger sample and 43.3% in the older sample. The obtained myopia prevalence rates are generally consistent with other European studies, as is the higher prevalence in female than male adolescents, accelerating with age. The high rates of uncorrected myopia warrant further investigation and should inform public health policies, including the implementation of regular refractive screenings.

This study is joint work with Lisa-Marie Tommes, Philipp Doebler and Sarah Weigelt, and is – in a revised version – published as an article in Frontiers in Medicine (2024:11, p. 1483069, https://doi.org/10.3389/fmed.2024.1483069). It has been reformatted to conform to the overall style of this dissertation.

2.1.1. Introduction

The global prevalence of myopia is increasing and has been estimated to become as high as 49.8% in 2050, if not for control interventions (Holden et al., 2016). In parts of East Asia, myopia prevalence has even reached alarmingly high rates of up to 90% in adolescents and young adults (Dolgin, 2015; Morgan et al., 2018), with high myopia being as high as 10-20% (Morgan et al., 2018). In Europe, both myopia and high myopia prevalence are considerably lower than in (East) Asia (Baird et al., 2020; Xiang & Zou, 2020). Yet, increases in myopia prevalence have been observed in Europe as well (Holden et al., 2016). As myopia can cause substantial individual and public financial burden (Flitcroft, 2012; Holden et al., 2014), and high myopia is associated with an increased risk of severe secondary pathologies (Saw et al., 2005), this global increase in myopia prevalence requires immediate attention.

Unfortunately, current European data on myopia prevalence are rather sparse. In two recent reviews on myopia epidemiology in school children (Grzybowski et al., 2020) and on epidemiological data on myopia from population-based studies (Xiang & Zou, 2020), only nine publications reporting myopia prevalence in Europe (geographical definition) were identified (Grzybowski et al., 2020; Xiang & Zou, 2020). Therein, myopia prevalence rates of school-aged children and adolescents vary between 2.4% (6-year-olds; Tideman et al., 2018) and 42.7% (10-19-year-olds; Matamoros et al., 2015). High myopia prevalence rates were consistently low (0%-<2%) in the three publications reporting them (Hagen et al., 2018; Harrington, Stack, & O'Dwyer, 2019; Matamoros et al., 2015). For Germany, a steady increase in myopia prevalence from 2.08% at age 3 to 25.87% at age 17 has been reported (Truckenbrod et al., 2021) – though again, data are sparse. To reduce this data gap, we investigated myopia epidemiology, including myopia prevalence, in school children in Germany.

With school age as a critical period for myopia development (Morgan & Rose, 2005; Myrowitz, 2012), several underlying factors might be target points for prevention and intervention. School myopia (or juvenile myopia) has been described to appear between the ages of 9 and 11, and to then progress up to the late teenage years or early twenties (Gilmartin, 2004). In a broader definition, school myopia is described to appear between the ages of 8 and 14 years, with potential further progression up to the age of approximately 30 (Morgan & Rose, 2005). Less bright (outdoor) light exposure and more near work are considered important environmental factors driving this development (Myrowitz, 2012). Furthermore, myopia prevalence and academic achievement are often connected in the literature. While the direction of causality has been a matter of debate, current evidence strongly suggests that education plays a causal role in myopia development (Baird et al., 2020), which is likely linked to both near work and light exposure (Rose et al., 2016). Regarding gender, in white and East Asian populations, myopia prevalence differences have

been found to appear around age 9 and become more pronounced thereafter, with a higher prevalence in girls than boys (Rudnicka et al., 2016). Up-to-date information on myopia prevalence, its development during school age and associated factors such as these is important for monitoring purposes and to create interventions for prevention and diagnostics of myopia (progression).

In this regard, uncorrected refractive errors are a most relevant issue as they are problematic in many ways, and they constitute the principal cause of visual impairments globally (Pascolini & Mariotti, 2012). In a recent meta-analysis, the global potential productivity loss associated with visual impairments due to uncorrected myopia has been estimated at USD $244 billion dollars, thereby substantially exceeding the cost of myopia correction (Naidoo et al., 2019). Uncorrected refractive errors have also been shown to affect children's educational outcomes. For example, children who were provided free glasses upon failing visual acuity screenings (and having improved visual acuity with refraction) improved in mathematics test scores. The analysis' effect size increased with increasing blackboard use during teaching, making it plausible for myopic children to have especially benefited from the provision of glasses, and underlining the impact of providing spectacles to myopic children (X. Ma et al., 2014). Thus, information on magnitude and associations of uncorrected myopia are important from a public health standpoint and may contribute to identifying relevant aspects regarding health education and diagnostic interventions.

Here, we performed non-cycloplegic autorefraction in two samples of school students in Germany. The samples constitute the upper and lower limit of the age range in which school myopia usually first appears. We aimed at estimating the prevalence of myopia and uncorrected myopia among primary and secondary school students in Germany and analyzing potential sociodemographic predictors for refractive status.

2.1.2. Methods

The study was approved by the local ethics board at TU Dortmund University and followed the tenets of the Declaration of Helsinki.

2.1.2.1. Participants

We recruited primary and secondary schools within the German federal state North Rhine-Westphalia, where children are usually six or seven years old when they enroll in primary school (grades 1-4). After that, most students visit one of four types of secondary schools: The general secondary school ("Hauptschule", grades 5-10) can be completed with the lower secondary school leaving certificate, the intermediate secondary school

("Realschule", grades 5-10) with the secondary school certificate, and the grammar school ("Gymnasium", grades 5-12 or 5-13) with the general qualification for university entrance (A-levels). Lastly, the comprehensive school ("Gesamtschule") combines all aforementioned courses of education and school-leaving certificates. The school system slightly differs between German federal states, but is generally comparable.

For each of these types of schools, we created randomized lists of all schools around a city in North Rhine-Westphalia, and contacted them accordingly. We chose the first six consenting primary schools and the first consenting secondary school per type for participation. Since no grammar school from the initial list agreed to participation, we contacted another grammar school located just outside the originally determined area, which participated. Subsequently, we invited all students of grades 3 and 4 (primary schools) as well as grades 8, 9, and 10 (secondary schools) to participate via a multilingual letter distributed two weeks prior to the testing date(s). Therein, families were told to inform the school if they did not want their child to participate.

Of the 581 eligible students for our younger sample (3^{th}- and 4^{th}-grade primary school students; S1), 489 participated. For our older sample (8^{th}-, 9^{th}-, and 10^{th}-grade secondary school students; S2), 1,344 students were eligible and 1,032 participated. Most of the eligible non-participating students were not at school during the testing dates due to Covid-19 related quarantine. One participant in S1 and two participants in S2 were excluded from all analyses, because we were unable to obtain the relevant measurements. Thus, the final sample comprised of 488 participants in S1 and 1,030 participants in S2.

2.1.2.2. Study Design

Data was collected at the schools between September and December 2021, i.e., during the first four months of the school year. To conduct all measurements, four trained experimenters visited each primary school for one day, and each secondary school for three consecutive days. In sum, 18 experimenters were involved in data collection. Participants completed the measurements individually, three at a time in the same room.

Upon participation, participants received a feedback card for their caregivers. All cards specified that we had measured refraction to detect ametropia. The other information varied based on our results: (1) If the participant had a visual aid, the family was reminded that regular visits to an ophthalmologist are advisable even in the absence of complaints. (2) If the participant had no visual aid and we detected no abnormalities, the family was informed about this and also told that regular visits to an ophthalmologist are advisable even in the absence of complaints. (3) If the participant had no visual aid and we detected abnormalities, the family was informed about this along with the recommendation to undergo an

ophthalmological examination. Cards (2) and (3) also explicitly stated that our measurements were not medical diagnoses. We did not include refractive values in the feedback.

2.1.2.3. Measurements

We measured non-cycloplegic refraction three times with one of three autorefractometers (2x model A12R with software 7.1.8.0, 1x model A09 with software 5.0.22.0; Plusoptix GmbH, Nürnberg, Germany) at a distance of 1 meter. The mean spherical equivalent refraction (sphere + ½ cylinder; SER) of these measurements was taken for analysis. If a participant wore glasses, we obtained their specifications by an auto lensmeter (model TL-3000C; Tomey Corporation, Nagoya, Japan). If a participant wore contact lenses during measurements, we recorded information about their kind.

We also recorded participant-reported gender (male/female/non-binary) and age in days, calculating the latter from the participant's birth date for immediate anonymization.

Furthermore, we obtained each school's social index level as a school-based measure of social burden (Schräpler & Jeworutzki, 2021). The social index is a measure to identify the need for support of individual schools in North Rhine-Westphalia due to the students' social composition. It is based on child and youth poverty as well as proportion of students with primarily non-German family language, who immigrated to Germany, and with special educational needs in learning, language, or emotional and social development. The social index is calculated on a scale from zero to 100 and each score is assigned to a social index level between one and nine, with one reflecting a low social burden (Schräpler & Jeworutzki, 2021).

2.1.2.4. Data Analysis

Data analysis was conducted using R 4.4.1 (R Core Team, 2021) in RStudio 2021.9.0.351 (RStudio Team, 2021) as well as the packages *psych* (Revelle, 2021), *mgcv* (Wood, 2017), *MuMIn* (Bartón, 2023), and *ggplot2* (Wickham et al., 2023). The significance level was set at $\alpha = 0.05$. If corrections were applied to calculations, e.g. for multiple comparisons, corrected p-values are reported.

2.1.2.4.1. Data Preparation

For four participants, we could only perform refractive measurements while they were wearing their glasses. We calculated their sphere and cylinder values by adding the respective glasses' specifications to the measured values. Then, we calculated mean SER as we did for the other participants.

Furthermore, we were not able to perform all three refractive measurements with some participants. If data from only one (two) measurement(s) were available, we used these data to calculate mean SER. For the right eye, this was the case for four (nine) participants, and for the left eye, for five (nine) participants, respectively.

Nine participants wore contact lenses during measurements and were thus excluded from all SER analyses.

Lastly, the autorefractometers have a measurement range from -7D to +5D SER in 0.25D steps for sphere and cylinder (Plusoptix GmbH, 2009, 2020). We replaced participants' values measured as "out of range" in the myopic (hyperopic) direction by -7.125D (+5.125D) SER as the next lower (higher) SER possible with the devices' 0.25D steps for sphere and cylinder. For the right eye, this was the case for seven (seven) participants, and for the left eye, for eight (nine) participants, respectively.

We tested the comparability between the measurements of the two autorefractometer models used for data collection in a comparison study: We measured 58 additional participants three times with each autorefractometer and calculated mean SER for each eye for each device. Paired t-tests, corrected with Holm's method for multiple comparisons (Holm, 1979), showed that the mean SER values obtained with the A09 device differed significantly from those of either A12R device (all ps < .001), while there was no difference between the A12R devices (both ps > .05). Visual inspection of LOWESS lines and Cronbach's Alpha with the devices as "items" (both eyes: $\alpha = .99$) indicated linear relationships between the mean SER values of all devices. Subsequently, we fitted generalized additive models including a smooth term to the comparison study data using the default generalized cross-validation to determine the degree of smoothness. The smooth used the usual wiggliness penalty of the second derivative, but no null space so that the F-test is a test of non-linearity. We predicted the mean SER of either A12R device for right and left eyes independently. As generalized cross-validation could potentially undersmooth, the same analysis was performed with the REML criterion as part of the sensitivity analysis. For all models, the smooth term was not significant (all ps > .05), again corrected for multiple comparisons using Holm's method (Holm, 1979). Therefore, we assumed a linear relationship between measurements with the A09 device and measurements with the A12R devices, and pursued a linear transformation of the A09 data to obtain comparable data for all participants from the actual study, regardless of the autorefractometer they had been measured with. To this end, we averaged the mean SER of the A12R devices for each participant in the comparison study, and fitted linear models to predict this averaged mean SER of the A12R devices from the mean SER of the A09 device for each eye. Finally, we linearly transformed the data from the actual study that had been measured with the A09 device with the obtained regression coefficients for each eye. Detailed results of the analyses mentioned in this

paragraph are presented in Supplementary Table A1-A5 and Supplementary Figure A1. In all following analyses, we used the linearly transformed data of the A09 device along with the (non-transformed) data of the A12R devices.

We rechecked all calculations reported in the results section (1) with the complete data without linear transformation of the A09 device data and (2) with the data from the A12R devices only (see Supplementary Table A6-A23 and Supplementary Information A1-A4). Despite a few quantitative and qualitative differences between the data analytic approaches, the overall results' patterns did not change.

Since the SER of the right and left eye were well correlated (Spearman's rho; $r_s = .82$, $p < .001$) and not significantly different from each other ($p = .12$), only data of the right eye are presented in the following.

2.1.2.4.2. Myopia Prevalence

We calculated myopia prevalence for S1 and S2 overall and for various subgroups. We defined myopia as SER ≤ -0.75D (Alsaif et al., 2019; Truckenbrod et al., 2021; Yotsukura et al., 2020) to compensate for myopia overestimation due to the non-cycloplegic nature of the autorefraction measurements. Myopia prevalence values are reported for this cut-off, if not stated otherwise. Prevalence rates for the SER ≤ -0.5D myopia definition are also reported for comparability with other investigations (Choy et al., 2020; Harrington, Stack, & O'Dwyer, 2019; Lundberg et al., 2018). High myopia was defined as SER ≤ -6D (Choy et al., 2020; Hagen et al., 2018; K. M. Williams, Verhoeven, et al., 2015).

For the myopia prevalence, we included all participants with usable SER data as well as participants without usable SER data, if we could derive the type of ametropia from their visual aid (i.e., measured or reported specifications). Usable SER data includes SER data obtained from successful autorefraction measurements from participants not wearing visual aids as well as successful autorefraction measurements over glasses, in which case we calculated the participants' actual SER as described earlier. Non-usable SER data therefore entails unsuccessful autorefraction measurements due to measurement complications or autorefraction measurements over contact lenses, in which case we could not determine the actual, uncorrected SER. Measurement complications entailing the absence of SER data only occurred in participants with visual aids. For one participant in S1 and two participants in S2, no SER data exists due to such complications, and we also do not have any information on their visual aid specifications. Thus, these three participants were excluded from analysis, as has already been described with regard to the participant sample. Further two participants in S1 and ten participants in S2 had no usable SER data, but we were able to derive their type of ametropia from their visual aids, and thus included them in the analyses on myopia prevalence.

For the prevalence estimation of high myopia, we only included participants with usable SER data since we could not always obtain detailed specifications of participants' visual aid and visual aid specifications do not always fit the magnitude of a refractive error.

2.1.2.4.3. Refractive Status Associations

An independent samples t-test was conducted to confirm SER differences between S1 and S2. Subsequently, we performed multiple linear regression analysis with SER as outcome for S1 and S2 separately, including grade and gender as predictors. Though age usually also predicts SER, we did not include both age and grade in the initial model as they are highly correlated (Spearman's rho; overall: r_s = .91; S1: r_s = .62; S2: r_s = .76). We included grade based on the assumption that years of schooling may play a role in myopia development and because e.g. Jianyong Wang et al. (2020) had found grade to predict myopia and vision impairment slightly better than age – which was also the case in our data for both S1 and S2. We subsequently applied the "all possible subsets" approach to test if there was a better regression model for either sample. Thereby, every possible predictor combination is run (automatically) to obtain the best combination of potential predictors – thus, this approach can be a useful screening to reduce the number of possible models (Z. Zhang & Wang, 2017). We tested age, gender, and grade as potential predictors and also included their interaction terms, constraining the inclusion of the latter in that they could only be included if the respective main terms already were. Both gender and grade were treated as categorical predictors.

We assessed the models obtained via the "all possible subsets" approach using adjusted R^2 and the Bayesian information criterion (BIC). Adjusted R^2 indicates the amount of variability of the dependent variable explained by a regression model. While R^2 always increases when more potential predictors are added to a model, irrespective of whether they add real predictive value, adjusted R^2 takes this potential overestimation into account and gives a more realistic estimation of the model's performance (Emerson, 2020). The BIC balances model fit and complexity. As models with more predictors always fit the data better than models with fewer ones, the BIC "penalizes" the addition of parameters to the model (Bauldry, 2015). In model selection, one aims maximizing R^2 and minimizing BIC.

In all regression analyses, we only included participants with available data for the considered predictors and the outcome. Furthermore, as there were only four non-binary participants, we only included males and females in these analyses. Post-hoc comparisons were conducted for significant predictors.

2.1.2.4.4. Uncorrected Myopia

To estimate the prevalence of participants with uncorrected myopia, we divided the number of myopic participants that reported absence of a visual aid by the number of myopic participants that reported either absence or presence of a visual aid. Thereby, we did not consider whether the specifications of participants' visual aids matched our refraction measurements nor whether the visual aid had actually been prescribed for myopia correction. We additionally performed the estimation of uncorrected myopia prevalence with a more conservative SER ≤ -1D myopia cut-off.

Furthermore, we exploratively investigated potential associations between uncorrected myopia and the schools' social index level in S1 by separately calculating the prevalence of uncorrected myopia for the three primary schools with the lowest and the highest social index level.

2.1.3. Results

In the following, results on myopia prevalence, associations with spherical equivalent, and the prevalence of uncorrected myopia will be presented. As described above, myopia was defined as SER ≤ -0.75D, and high myopia as SER ≤ -6D. Additionally, myopia prevalence rates are reported for the SER ≤ -0.5D cut-off.

The final sample included 488 participants in S1 (mean age: 9.30±0.78 years; gender: 266 male, 219 female, 3 n/a) and 1030 participants in S2 (mean age: 14.99±1.12 years; gender: 571 male, 454 female, 4 non-binary, 1 n/a). The number of participants included in the individual analyses is stated throughout in the following.

2.1.3.1. Myopia Prevalence

As expected, myopia prevalence was higher in the older than the younger sample: In our sample of children aged 9.30±0.78 years (S1), myopia prevalence was 8.4%, while in our sample of children aged 14.99±1.12 years (S2), myopia prevalence was 19.5%. High myopia was extremely low, affecting only two children (0.4%) in S1 and eight children (0.7%) in S2, respectively, which aligned with our expectations as well.

Furthermore, and also unsurprisingly, myopia prevalence was higher in higher versus lower grades: In our younger sample (S1), myopia prevalence was 8.2% in grade 3 and 8.6% in grade 4, and in our older sample (S2), it was 11.6% in grade 8, 21.5% in grade 9, and 25.7% in grade 10, respectively. Accordingly, the prevalence difference was particularly notable between grades 8 and 9. High myopia only occurred in one participant per grade in S1. In S2,

the relative frequency of high myopia slightly increased with increasing grade level, but again, extremely few participants were affected: one in grade 8, two in grade 9, and five in grade 10. Table 2.1 displays myopia and high myopia prevalence rates per sample and grade in detail.

Table 2.1

Myopia and High Myopia Prevalence in S1 and S2 Overall and by Grade

	Myopia				high myopia
sample	**age *M*(*SD*)**	***N***	**% ≤ -0.75D**	**% ≤ -0.5D**	**% ≤ -6.0D**
S1	9.30 (0.78)	488	8.4	11.3	0.4
grade 3	8.85 (0.73)	245	8.2	10.2	0.4
grade 4	9.75 (0.53)	243	8.6	12.3	0.4
S2	14.99 (1.12)	1,030	19.5	28.8	0.7
grade 8	13.98 (0.77)	346	11.6	18.2	0.3
grade 9	15.04 (0.80)	349	21.5	30.1	0.6
grade 10	15.97 (0.73)	335	25.7	38.5	1.2

Note. Age and *N* are presented for the sample included in the myopia prevalence calculation. For the high myopia prevalence calculation, 2 (10) of these participants were excluded from S1 (S2) as described in Data Analysis. Thus, 486 participants (age: 9.29±0.77 years) were included in the high myopia prevalence calculation for S1, and 1020 participants (age: 14.98±1.12 years) for S2.

We also discovered interesting results with regard to gender: As presented in Table 2.2, myopia prevalence for males was 7.5% and for females 9.6% in our younger sample (S1), while it was 14.9% for males and 24.9% for females in our older sample (S2). Thus, while myopia prevalence was comparable between genders in S1, many more females than males exhibited myopia in S2. High myopia occurred relatively more often in males than females in both samples (see Table 2.2). A higher prevalence of myopia in adolescent females than males is expected, but the gender differences in S2 are surprisingly large, as will be presented in the following.

Table 2.2

Myopia Prevalence in S1 and S2 by Gender

		Myopia		high myopia
sample	**age *M*(*SD*)**	***N***	**% ≤ -0.75D**	**% ≤ -0.5D**	**% ≤ -6.0D**
S1					
female	9.27 (0.77)	219	9.6	11.0	0.0
male	9.33 (0.79)	266	7.5	11.7	0.8
S2					
female	14.90 (1.05)	454	24.9	33.3	0.4
male	15.05 (1.17)	571	14.9	25.0	0.9

Note. Four participants with unknown gender and four non-binary participants were excluded from these calculations. Age and *N* are presented for the sample included in the myopia prevalence calculation. For the high myopia prevalence calculation, 2 (10) of these participants were excluded from S1 (S2) as described in Data Analysis. Thus, 483 participants (age: 9.30±0.78 years) were included in the high myopia prevalence calculation for S1, and 1015 participants (age: 14.98±1.12 years) for S2.

The accelerating gender difference with increasing age can be seen even more clearly in individual grades: Not only was the myopia prevalence (overall and in individual grades) in females higher than in males in the older sample (S2), but the between-grade prevalence differences were also more pronounced in females than in males (see Figure 2.1): The prevalence difference between grade 8 and 9 is comparable for males (9.0%) and females (10.4%), but there is a 22.4% higher myopia prevalence for females in grade 10 than 8, while the prevalence of males in grade 10 is only 6.5% higher than of those in grade 8. Interestingly, while myopia prevalence was virtually similar between genders in grade 3 (1.7% higher for males), a higher prevalence in females than males already emerged in grade 4, where the between-gender difference (5.9%) was even higher than in grade 8 (4.1%) and 9 (5.5%). Strikingly, in grade 10, females exhibited a 20.0% higher myopia prevalence than males. Males were slightly, though non-significantly (all Holm-corrected *ps* > .05; Holm, 1979), older than females in all grades of S2 – thus, age differences between genders do not underly the higher myopia prevalence in females.

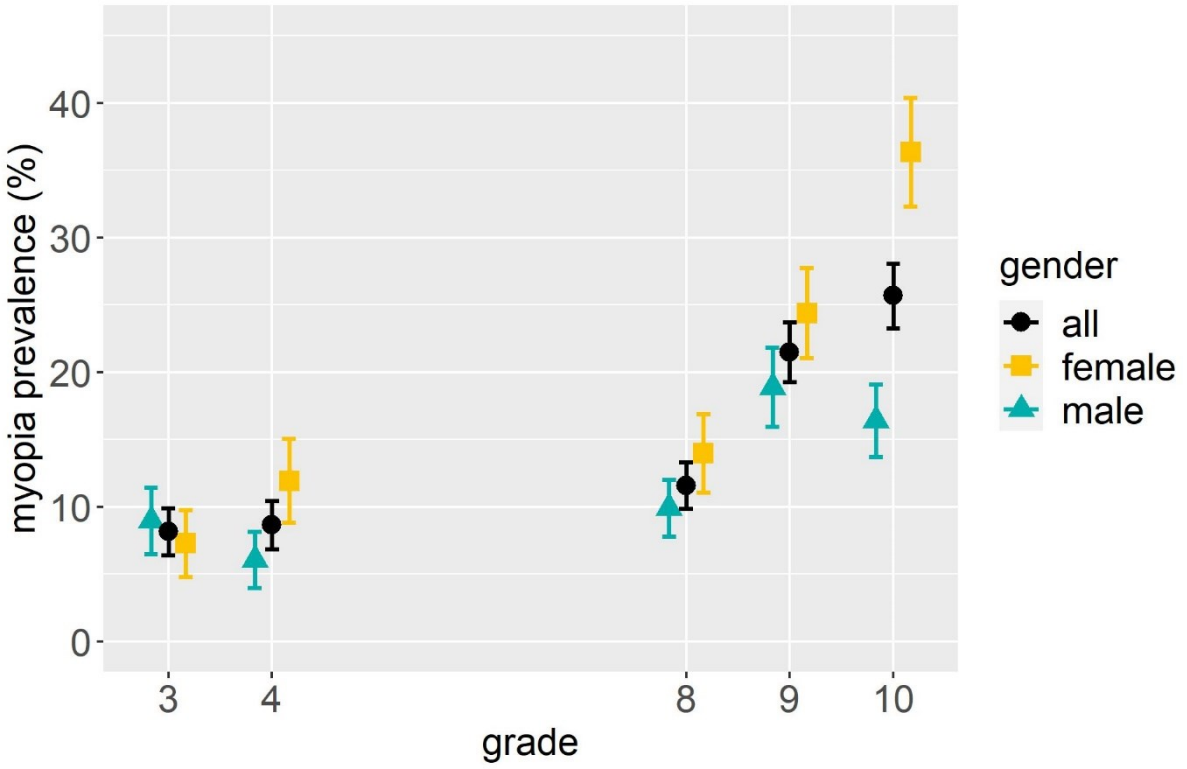

Figure 2.1. Myopia prevalence and standard error per gender by grade. The data for all genders include eight more participants than the data of males and females combined due to four non-binary participants and four participants with unknown gender.

As myopia is often linked to academic achievement in the literature, we also examined myopia prevalence in the different schools – and thus school types – in the older sample (S2; see Table 2.3). Sorted from lowest to highest-level school leaving certificate that can be achieved at the respective schools, we found a 3.1% lower myopia prevalence in the general secondary school than in the intermediate secondary school, whose myopia prevalence was virtually the same as in the grammar school. Interestingly, the comprehensive school – offering all school leaving certificates – exhibited the highest myopia prevalence, which was even 3.2% higher than that in the grammar school. Thus, no clear picture emerged, as between-school differences – albeit following the order one might expect – were only marginal, and the comprehensive school exhibited the highest myopia prevalence. Please note the higher age of participants in the general secondary school (see Table 2.3). The same picture emerged for all grades individually.

Table 2.3

Myopia Prevalence in S2 by School

	Myopia				high myopia
sample	**age *M*(*SD*)**	***N***	**% ≤ -0.75D**	**% ≤ -0.5D**	**% ≤ -6.0D**
GSS	15.61 (1.14)	218	16.1	21.6	1.4
ISS	14.93 (1.03)	308	19.2	29.9	0.3
CS	14.71 (1.05)	287	22.6	34.1	0.0
GS	14.82 (1.06)	217	19.4	27.6	1.4

Note. Age and *N* are presented for the sample included in the myopia prevalence calculation. For the high myopia prevalence calculation, 10 participants were excluded as described in Data Analysis. The age of participants included in the high myopia calculation was comparable to those included in the myopia calculation (see Table 2.1). GSS = general secondary school, ISS = intermediate secondary school, CS = comprehensive school, GS = grammar school.

Regarding individual grades per school type in the older sample (S2), there was again no clear picture, but an interesting pattern (see Figure 2.2): While myopia prevalence was higher for grade 10 than 8 in all schools, the magnitude of this difference varied, with the grammar school exhibiting the largest prevalence difference by far as well as the lowest myopia prevalence of all schools in grade 8. This is somewhat consistent with the frequently reported link between academic achievement and higher myopia prevalence. These findings should, however, be considered with caution, and need further investigation in a sample including more than one school per school type – as e.g. social index levels varied between schools and may pose potential confounders.

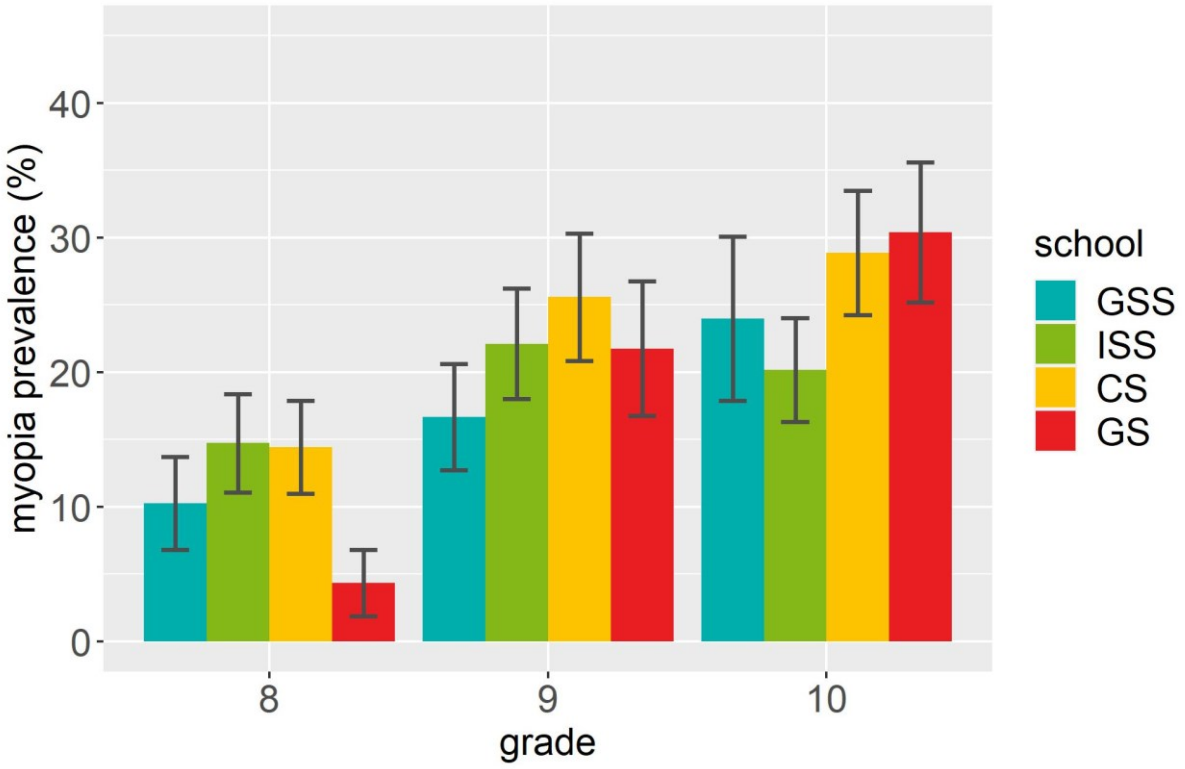

Figure 2.2. Myopia prevalence and standard error per school by grade in S2. GSS = general secondary school, ISS = intermediate secondary school, CS = comprehensive school, GS = grammar school.

2.1.3.2. Refractive Status Associations

To consider a continuous variable sensitive to a person's myogenic development prior to becoming myopic, we conducted further analyses with the SER, which was significantly more myopic in the older (S2, N = 1,029) than the younger (S1, N = 486) sample (p < .001; S1: M = 0.08D, SD = 1.06D; S2: M = -0.37D, SD = 1.20D). Figure 2.3 displays the mean SER per gender by grade. In concordance with the prevalence data presented in Figure 2.1, a more myopic SER is visible in higher than lower grades. Furthermore, a substantial mean SER difference of almost 0.4D between females and males is apparent in grade 10, with the females' mean SER being more myopic.

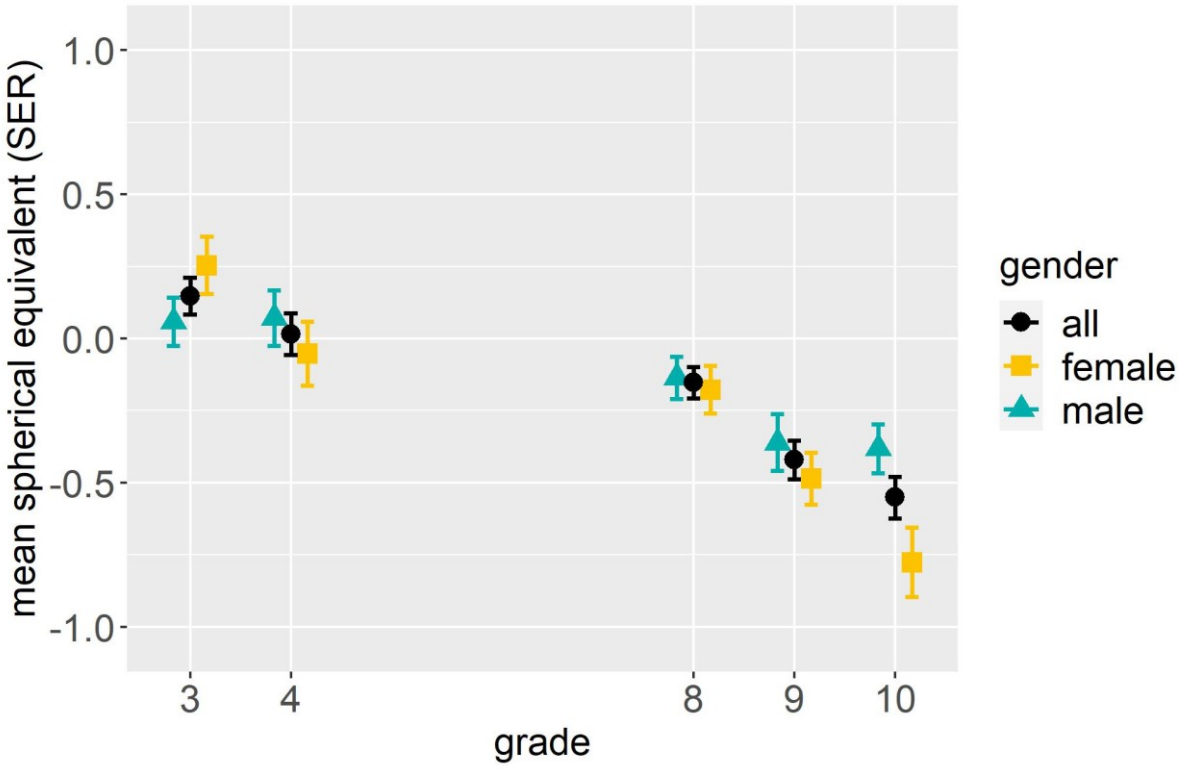

Figure 2.3. Mean SER and standard error per gender by grade. The data for all genders include eight more participants than the data of males and females combined due to four non-binary participants and four participants with unknown gender.

Using multiple regression analysis, we found no associations with SER in the younger sample (S1, N = 483): The model with the predictors grade and gender did not reach statistical significance (R^2 = .004, p = .371). In the "all possible subsets" approach, the best-fitting model did not include any of the given predictors. The best-fitting model that included predictors and exhibited the lowest BIC and a comparatively high adjusted R^2 (see chapter 2.1.2.4.3 for an explanation of the statistical terms) included only grade as predictor, but did not reach statistical significance (R^2 = .004, p = .175).

In the older sample (S2, N = 1,015), both grade and gender were significant predictors of SER (see Table 2.4; model A), with the respective model being overall significant (R^2 = .025, p < .001). This model was also identified as most promising via the "all possible subsets" approach. It exhibited the second-lowest BIC, which was only minimally higher than the lowest one, and the highest adjusted R^2 within a reasonable BIC range. The first model with a higher adjusted R^2 than model A included grade, gender and grade × gender as predictors (model B). It was thus also fitted, despite a substantial BIC difference to model A. Model B explained variance in SER (R^2 = .029, p < .001), but while grade was a significant predictor (grade 9: p = .023; grade 10: p < .001), gender and both grade × gender terms were not

significant. Lastly, an F-test for nested models showed that model B did not fit the data better than model A (p = .139).

Subsequent data inspection revealed a more myopic SER in females than males in S2 (females: M = -0.48D, SD = 1.22D, males: M = -0.29D, SD = 1.17D). Regarding grade, post-hoc Welch two sample t-tests (corrected with Holm's method for multiple comparisons; Holm, 1979) showed that the SER of grade 9 (M = -0.42D, SD = 1.25D) and grade 10 (M = -0.55D, SD = 1.29D) participants was significantly more myopic than that of grade 8 participants (M = -0.15D, SD = 1.02D; grade 8 vs. 9: p = .004; grade 8 vs. 10: p < .001). There was no significant difference between the SER of grade 9 and 10 participants (p = .183). Detailed statistical parameters for the calculations reported in this section are presented in Supplementary Information A5.

Table 2.4

Coefficient Estimates of the Multiple Linear Regression Model A for S2

coefficient	*B*	95% CI	SE	*t*	*p*
intercept	-0.26	[-0.41, -0.11]	0.08	-3.36	< .001
grade (9)	-0.26	[-0.43, -0.08]	0.09	-2.83	.005
grade (10)	-0.40	[-0.58, -0.22]	0.09	-4.32	< .001
gender	0.18	[0.04, 0.33]	0.08	2.44	.015

Note. CI = confidence interval, SE = standard error.

These results are in line with those on myopia prevalence rates (cf. Figure 2.1) and indicative of gender differences in myopic development being more present in older than younger children. Furthermore, grade significantly predicting SER in the older sample (S2), but not the younger one (S1), is consistent with the acceleration of myogenic development in teenage years. Yet, it should be noted that S1 encompassed two grades, and S2 three, thus impeding between-sample comparisons with regard to results on grade. Detailed results of the "all possible subsets" analyses can be found in Supplementary Table A24 & Supplementary Table A25.

2.1.3.3. Uncorrected Myopia

Shockingly, 51.2% of the 41 myopic participants in our younger sample (S1), and 43.3% of the 201 myopic participants in our older sample (S2) reported no visual aid. For the more conservative SER ≤ -1D myopia cut-off, these numbers were still as high as 48.7% (S1)

and 32.7% (S2). These values are also presented in Table 2.5, together with the prevalence rates of uncorrected myopia per grade, showing that while there is some variation between grades, said prevalence does not systematically change with increasing grade, but is relatively stable across grades. Furthermore, Figure 2.4 shows the prevalence of corrected and uncorrected myopia per grade relative to the overall sample. It is readily apparent that based on the overall sample, the prevalence of uncorrected myopia is increased in higher compared to lower grade level, cumulating in more than 10% of all grade 10 participants having uncorrected myopia.

Table 2.5

Prevalence of Uncorrected Myopia in S1 and S2 Overall and by Grade

	myopia cut-off SER ≤ -0.75D		**myopia cut-off SER ≤ -1D**	
sample	***N***	**% uncorrected**	***N***	**% uncorrected**
S1	41	51.2	39	48.7
grade 3	20	55.0	18	50.0
grade 4	21	47.6	21	47.6
S2	201	43.3	159	32.7
grade 8	40	50.0	29	37.9
grade 9	75	38.7	61	29.5
grade 10	86	44.2	69	33.3

Note. N indicates the number of myopic participants per the respective cut-off. The prevalence indicates the percentage of myopic participants without visual aids based on all myopic participants.

With regard to gender, the prevalence of uncorrected myopia was 55.0% for males and 47.6% for females in the younger sample (S1), and 44.7% for males and 42.5% for females in the older sample (S2). With the SER ≤ -1D myopia cut-off, these numbers were 52.6% (30.8%) for males and 45.0% (34.1%) for females in S1 (S2). Thus, the pattern we found for myopia prevalence regarding grade and gender does not emerge for the prevalence of uncorrected myopia (based on all myopic participants).

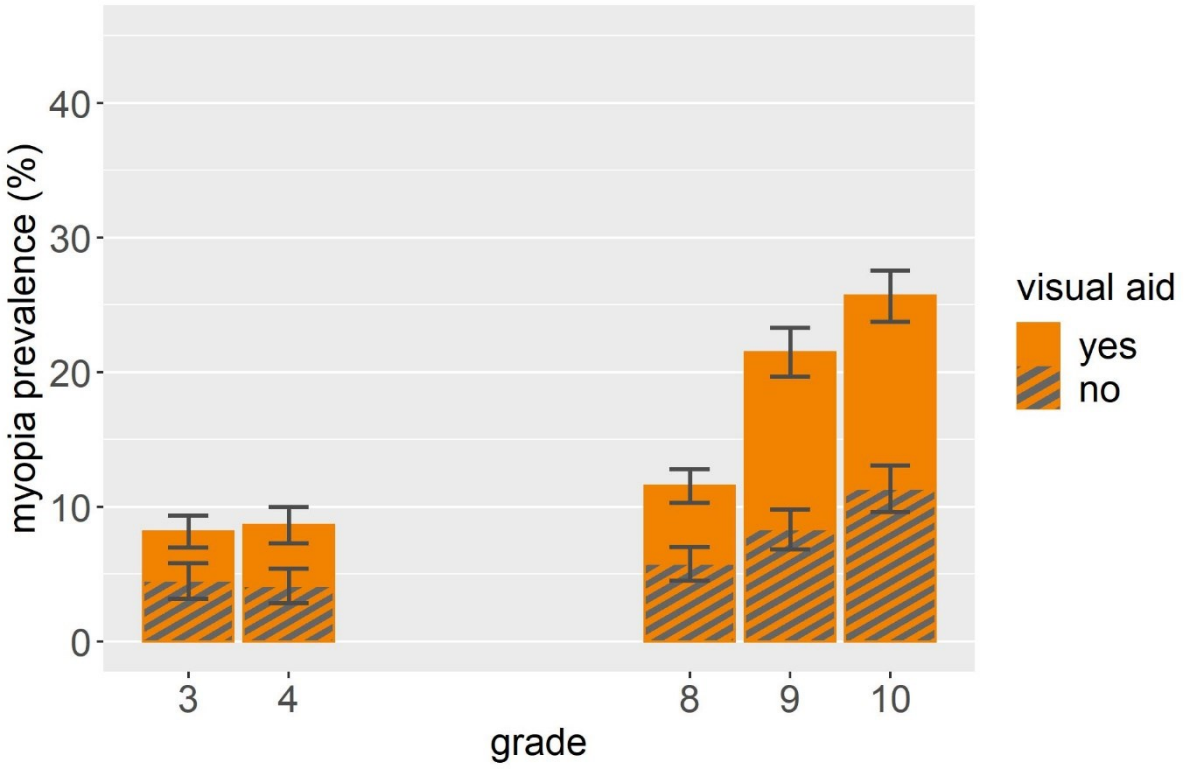

Figure 2.4. Corrected and uncorrected myopia prevalence and standard error by grade relative to the overall sample.

Lastly, of the myopic participants in the younger sample (S1), 38.9% (7 of 18) in the three schools with the lowest social index levels – i.e., lower social burden – and 60.9% (14 of 23) in the three schools with the highest social index levels – i.e., higher social burden – were uncorrected. This was only assessed in S1, as social index level is confounded with type of school in S2. Since data on (un)corrected myopia in S1 are based on 41 myopic participants only, this finding should be considered with caution and warrants replication.

2.1.4. Discussion

We investigated myopia prevalence, potential associations with SER, and prevalence of uncorrected myopia in school students in Germany. Myopia prevalence was 8.4% for grade 3-4 primary school students (S1) and 19.5% for grade 8-10 secondary school students (S2), with a substantial difference between grade 8 (11.6%) and grades 9 (21.5%) and 10 (25.7%). Apart from one exception, myopia prevalence was higher in higher versus lower grades for all schools in S2 – but the magnitude of this difference varied between schools, and thus types of schools. The grammar school exhibited the largest prevalence difference between grades 8 and 10. In S2, we also found a 10% higher myopia prevalence in females than males, with a higher magnitude of the gender difference in higher than lower grades. Neither age, gender,

grade nor their interactions predicted SER in multiple linear regression analyses for S1. For S2, the model with grade and gender performed best, with more myopic SER in grades 9 and 10 than in grade 8 as well as in females than males. In S1, 51.2% of myopic participants were uncorrected, as were 43.3% in S2. More than 10% of the total grade 10 sample exhibited uncorrected myopia. Schools with a lower social burden exhibited a lower percentage of uncorrected versus corrected myopic participants than schools with a higher social burden in S1.

Table 2.6 presents myopia prevalence rates in children and adolescents from this study as well as other recent German and European investigations. The other German investigations (Kaymak et al., 2022; Truckenbrod et al., 2021) report prevalence rates largely similar to the present ones – although one study yielded a 22% myopia prevalence in grade 5-7 grammar school students (Kaymak et al., 2022). This is interesting as participants in the respective study (Kaymak et al., 2022) were younger than those in our S2, and we measured an extremely low myopia prevalence in grade 8 grammar school students (4.3%, see Figure 2.2). Methodological differences might have played a role: In contrast to our opt-out procedure, active parental consent was conditional for participation in the respective study (Kaymak et al., 2022). Furthermore, while in said study, refraction was also measured objectively without cycloplegia, the myopia cut-off was more liberal than ours, and additional subjective refraction was often performed (Kaymak et al., 2022). Despite these differences that might benefit from further investigation, current data from Germany are generally consistent with our results.

Results from many of the other European investigations are also overall in agreement with ours (Harrington, Stack, & O'Dwyer, 2019; Lundberg et al., 2018; Popović-Beganović et al., 2018; Tideman et al., 2018; L. Yang et al., 2020), especially considering methodological differences and the usual myopia prevalence increase during school age. Likewise, the low prevalence of high myopia in our data is consistent with the few other publications investigating high myopia (Hagen et al., 2018; Harrington, Stack, & O'Dwyer, 2019; Matamoros et al., 2015).

Table 2.6

Myopia Prevalence Rates Reported in This and Other European Studies

country	cycloplegia	myopia cut-off (SER)	age (years)	sample size	myopia (%)
Germany (present study)	no	≤ -0.75D	9.30 (0.78)	488	8.4
		≤ -0.5D			11.3
		≤ -0.75D	14.99 (1.12)	1,030	19.5
		≤ -0.5D			28.8
Germany (Kaymak et al., 2022)	no	≤ -0.5D	11.2 (1.1)	274	22.3
Germany (Truckenbrod et al., 2021)	no	< -0.75D	8	342	3.9
			9	366	6.9
			10	349	11.1
			13	334	21.7
			14	301	22.8
			15	279	23.6
			16	213	26.4
Austria (L. Yang et al., 2020)	no	< -0.5D	15-<18	1,507,063	24.8 (males)
Bosnia and Herzegovina (Popović-Beganović et al., 2018)	yes	≤ -0.5D	8	88	7.9
			9	123	7.3
			10	119	14.3
			13	114	21.5
			14	113	23.4
			15	101	28.2
			16	103	29.6

Table 2.6 – Continued

Myopia Prevalence Rates Reported in This and Other European Studies

Denmark (Lundberg et al., 2018)	yes	≤ -0.5D	15.4 (0.7)	307	17.9
	no				33.6
France (Matamoros et al., 2015)	yes	≤ -0.5D	0-9	1,489	19.6
			10-19	8,289	42.7
Ireland (Harrington, Stack, & O'Dwyer, 2019)	yes	≤ -0.5D	6.7 (0.49)	728	3.7
			12.8 (0.48)	898	22.8
Netherlands (Tideman et al., 2018)	yes	≤ -0.5D	6	5,711	2.4
Norway (Hagen et al., 2018)	yes	≤ -0.5D	16	246	11.0
Poland (Czepita et al., 2019)	yes	≤ -0.5D	≥6-<9	4,875	3.65 (boys) 3.35 (girls)
			≥9-<13		5.71 (boys) 8.30 (girls)
			≥13-<16		5.96 (boys) 10.37 (girls)
Spain (Alvarez-Peregrina et al., 2019)	no	< -0.5D	6.19 (0.78)	1,993	19.1

Note. The studies are chosen due to them reporting data from Germany (Kaymak et al., 2022; Truckenbrod et al., 2021) or their inclusion in one of the reviews discussed earlier (Grzybowski et al., 2020; Xiang & Zou, 2020). Data for the age groups corresponding best to the present study's samples (S1: ca. 8-10 years; S2: ca. 13-16 years) are reported. In Alvarez-Peregrina et al. (2019), data from 2016 and 2017 is reported, of which only the latter is included here. Age is reported as mean (SD) if possible. Otherwise, the age range is reported. Note that the publications partly differ in methodological aspects not reported here. For example, different methods have been used to assess refractive status, and the eyes on which the myopia cut-off was applied to vary (e.g., left, right, both, either), which may account for some variation in prevalence rates.

Some European studies, however, differ more strongly from ours, yielding both lower (Czepita et al., 2019; Hagen et al., 2018) and higher myopia prevalence rates (Alvarez-Peregrina et al., 2019; Matamoros et al., 2015). One reason could be methodological differences: The much higher prevalence in Alvarez-Peregrina et al. (2019) may partly be accounted to the fact that while in both, theirs and our study, non-cycloplegic measurements were taken, Alvarez-Peregrina et al. (2019) used a myopia cut-off of < -0.5D SER. But even with a ≤ -0.5D cut-off, myopia prevalence in our S1 is still considerably lower than in their sample, despite the latter being younger. The authors suggest a potential bias due to their campaign offering free glasses if needed (Alvarez-Peregrina et al., 2019). Matamoros et al. (2015) also report much higher prevalence rates than our study or others from Europe. Their data stem from eye clinics dedicated to refractive errors, so there may again be participation bias (Matamoros et al., 2015). Despite methodological aspects potentially explaining some differences, myopia prevalence likely also varies between countries based on other factors, and more research is needed to uncover those. This is especially important in light of the Covid-19 pandemic, as a recent meta-analysis shows accelerated myopic progression during compared to before the pandemic (Watcharapalakorn et al., 2022).

Regarding gender, we found a higher myopia prevalence and more myopic refractive status in females than males in our older sample (S2). This corresponds to prior results: One study e.g. found a similar SER for Polish boys and girls before the age of 9, but lower a SER and higher myopia prevalence in females than males after that (Czepita et al., 2019). In their review, Rudnicka et al. (2016) conclude that in white (and East Asian) populations, gender differences in myopia prevalence emerge around the age of 9 and become more pronounced thereafter. We also observed a higher between-gender prevalence difference among the older (grade 10) than younger (grade 8) participants in our S2. Furthermore, when adding grade × gender interactions to our regression model for predicting SER in S2, the interaction term for grade 10 was close to significance (see Supplementary Information A5) – even though the model did not outperform the model without the interaction. Our data thus support the notion of more pronounced gender differences in myopia prevalence in older than younger adolescents.

Further interesting observations regarding grade were made. Firstly, we found a markedly higher myopia prevalence difference between grades 8 and 9 than grades 9 and 10. Furthermore, the prevalence in grade 8 is only 3% higher than in grade 4, but 9.9% lower than in grade 9. While grades 8 and 9 lie at the upper end or even beyond the 8-14 years of age during which school myopia typically appears (Morgan & Rose, 2005), this result indicates that a large portion of myopia onset may happen between grades 8 and 9 in a German-like school system (with school entry at age 6 or 7). Although this should ideally be tested longitudinally, the present study did include a high number of participants. Considering the

economic and personal burdens associated with uncorrected and/or high myopia (Naidoo et al., 2019; Saw et al., 2005), this may well have public health implications. It may for example be reasonable to implement routine myopia assessments or health education on the importance of refractive correction in grade 9. During data collection, many uncorrected myopic participants in our older sample (S2) confirmed not seeing well, but expressed unwillingness to wear a visual aid due to concerns about their appearance and their peer group's reaction – while at the same time having virtually no knowledge on myopia (implications). Thus, it may be helpful to target peer groups with interventions tailored to adolescents' specific needs.

Secondly, the difference in myopia prevalence between grades 8 and 10 is especially pronounced for the grammar school, which offers the highest school leaving certificate, and also exhibits the lowest prevalence in grade 8 compared to the other secondary schools. This finding cannot be attributed to younger age of grammar school students: Students' age was similar between all secondary schools but the general secondary school. If there is, in fact, a lower myopia prevalence in grade 8 grammar school students compared to other students, uncovering the underlying factors would be interesting. Yet, a much higher myopia prevalence for even younger grammar school students in Germany has also been reported (Kaymak et al., 2022), so this finding is far from conclusive. Meanwhile, we generally found little prevalence difference between secondary schools, which is maybe expected, since our participants from different schools but within the same grades had generally visited school for the same amount of years. The commonly reported link between academic achievement and myopia may be more pronounced later in life, when time spent on schooling differs more between people pursuing higher education versus not. Yet, students in Chinese elementary key (i.e., university-oriented) schools exhibited a higher myopia prevalence than students in less academically oriented, non-key schools – with a similar prevalence in grade 1, but a faster acceleration in key than non-key schools thereafter (Thorn et al., 2020) – showing that there can be potentially education-related myopia prevalence differences even between students of similar grades. This result somewhat mirrors our finding of the highest between-grade prevalence difference in grammar school compared to other schools. Importantly, only one secondary school per school type was included in the investigation, and the calculations' standard errors were large (see Figure 2.2). Said findings should thus be considered preliminary indications, as they may also be a result of other between-school differences. Still, they indicate potential interactions between school type, grade and myopia, which should be investigated further in samples better suited for respective analyses.

A striking finding of this investigation is the high prevalence of myopic participants that were uncorrected – specifically, 51.2% of myopic participants in our younger sample (S1) and 43.3% of myopic participants in our older sample (S2) did not have or report having a visual aid. Even when only considering participants with SER ≤ -1D, rates of uncorrected

myopia were still 48.7% (S1) and 32.7% (S2). High rates of uncorrected and/or undetected myopia have been reported elsewhere: In a sample of Hong Kong primary school students (grade 1-6), only 23.6% of parents knew about their child's refractive error (Choy et al., 2020). In Eastern China, 34.5% of myopic participants ranging from kindergarten to high school did not wear glasses (Jianyong Wang et al., 2020), and in 6-8- and 11-13-year-olds in Canada, the rate of myopic participants that were uncorrected was also 34.5% (M. Yang et al., 2018). In 7-16-year-olds in Bosnia and Herzegovina, 54.5% of the study population required, but did not have refractive correction (Popović-Beganović et al., 2018). These troubling results underline the necessity of early and repeated myopia screenings, which may contribute to reducing the high amount of visual impairments attributable to uncorrected refractive error (Naidoo et al., 2019). While there are mandatory vision screenings for school-aged children in some countries – for example, 41 US states require a vision screening for school-aged children, with between-state variation regarding frequency and timing (Antonio-Aguirre et al., 2023; Wahl et al., 2021) – this is not the case everywhere. In Germany, a vision screening is conducted in the mandatory school entry examination prior grade 1 (around age 6). Only a few federal states have mandatory health examinations including a vision screening at some point during school age after that. The next nationwide mandatory vision screening is conducted when attempting to obtain a driver's license (usually around the ages 16-18; though it is of course not mandatory to obtain a driver's license). Considering the high prevalence of uncorrected myopia reported for school-aged children, the frequent lack of mandatory vision or refractive screenings is of concern – especially since school myopia onset usually lies between the ages of 8 and 14 years (Morgan & Rose, 2005), and the absence of routine eye checks has been identified as a risk factor of myopia development in school students (Choy et al., 2020). Therefore, refractive screening at school age would be highly advisable. Given the large prevalence difference between grade 8 and 9 in the present study, these screenings should not discontinue before grade 9 – but should also be performed in (later) adolescence. As stated before, education about refractive errors, their potential consequences and correction could also be helpful to raise societal awareness, and might with appropriate peer group interventions increase adolescents' acceptance of visual aids.

Lastly, the rate of myopic participants without correction was 22% lower in primary schools with low than in those with high social burden. While these results are preliminary and the low sample size should be considered when interpreting them, it may be worthwhile to test potential associations between uncorrected myopia and social burden in a larger sample. If such a result can in fact be replicated, this may be another potential aspect one could incorporate in the planning of refractive screenings or health education with regard to refractive errors.

2.1.4.1. Strengths and Limitations

A strength of this study is sample representativeness, achieved through contacting schools in the area in a random order and an inclusion of the different types of schools. Among others, the variance in social index levels confirms some variability between participating schools. Representativeness was further increased by using non-invasive autorefraction and immediate data anonymization – as therefore, the need for informed parental consent was waived by the ethics committee. Instead, an opt-out procedure was used in that participants or their caregivers could refuse participation. Had we used more invasive methods, for example cycloplegia, active parental consent would have been necessary. This would most likely have entailed a significantly lower participation rate as well as a participation bias, with a potential underrepresentation of specific social groups.

On the other hand, the use of non-cycloplegic refraction measurements also poses a limitation of our study, since they have been shown to measure a more myopic SER and thus overestimate myopia as compared to cycloplegic refraction measurements (Grzybowski et al., 2020; Rudnicka et al., 2016). However, good measurement accuracy has been reported for non-cycloplegic measurements with Plusoptix devices before, especially in non-hyperopic individuals (Fogel-Levin et al., 2016; Ghadimi et al., 2024; Payerols et al., 2016; Teberik et al., 2018). For example, in children as young as 7.63±3.41 years, the mean SER of non-cycloplegic Plusoptix A12 measurements was only 0.43D more myopic than that of cycloplegic refraction measurements. Thereby, the mean difference between Plusoptix and cycloplegic measurements was -0.048D for the myopic and 0.37D for the hyperopic spherical component (Fogel-Levin et al., 2016). A recent systematic review and meta-analysis confirms a generally reasonable agreement between non-cycloplegic Plusoptix measurements and cycloplegic measurements (Wilson et al., 2022). Taken together with the fact that the difference between cycloplegic and non-cycloplegic measurements is both higher in younger than older participants (Rudnicka et al., 2016) and especially strong in more hyperopic individuals (Fotedar et al., 2007; Krantz et al., 2010; Sanfilippo et al., 2014) as well as our use of a ≤ -0.75D SER myopia definition, we assume that the use of non-cycloplegic measurements did not overly distort our prevalence estimates in our older sample (S2). In younger participants, deviations of non-cycloplegic from cycloplegic measurements are generally larger. Yet, investigations showing a good measurement accuracy of non-cycloplegic Plusoptix measurements and reasonable agreement with cycloplegic refraction were often conducted with young participants (Fogel-Levin et al., 2016; Wilson et al., 2022). Also, the participants classified as myopic in our younger sample (S1) had a mean SER of -2.52D±1.41D, with > -1D in only two participants. We thus suspect that the overestimation of myopia prevalence in our S1 was not as grave either.

Another limitation is the inclusion of only one secondary school per school type, which gravely limits the informative value of results regarding different types of schools, as the respective schools also differed in characteristics like their social index levels. Yet, we did not want to omit the findings regarding the different schools in S2, but we explicitly emphasize that they may be confounded and should be interpreted as tentative, non-conclusive indications.

Lastly, the detected measurement differences between the two autorefractometer models are of course very unfortunate. We have taken steps to correct for these by linearly transforming the data from the deviating device and the additional analyses in the Supplementary Materials confirm that, both compared to the data before the linear transformation and to the data when the deviating device is excluded, the results do not show much change. Thus, while this circumstance is undesirable and should be avoided in the future, there is likely no major impact from the between-model deviation.

2.1.4.2. Conclusion

The 8.4% prevalence we observed for 3rd- and 4th-graders (S1) as well as the 19.5% prevalence we observed for 8th-, 9th- and 10th-graders (S2) in Germany are generally in line with other European investigations. Furthermore, the higher prevalence and more myopic SER in S2 than S1 as well as in higher versus lower grades within S2 was as expected. With regard to specific grades, our results show that grades 8 and 9 – i.e., around the ages 13-15 – seem to be an important time with regard to myopia onset. In accordance with other investigations, our data also demonstrate a higher myopia prevalence and a more myopic refractive status in females than in males in the older sample, accelerating with increasing grade. Lastly, we found a strikingly high proportion of uncorrected (versus corrected) myopia in both samples, and more than 10% of the complete grade 10 sample had uncorrected myopia. These drastic results warrant further consideration and call for interventive measures. Generally, our findings entail important implications for public health – specifically, they underline the necessity of mandatory refractive screenings and health education on the implications of myopia for school-aged children and adolescents.

2.1.5. Acknowledgements

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2.1.6. Disclosure of Interest

The authors declare that they have no competing interests.

2.2. Study 2:

Participant Recruitment for Online Research – Lessons From a Parent Questionnaire Study on Children's Spectacle Ownership

Abstract: Various strategies can be used to recruit participants for online research. These recruitment strategies can differ in various aspects like recruitment success, sample representativeness or workload, and they might also influence research outcomes. Thus, one needs to carefully consider which ones to use for an investigation, and in this context, more knowledge on various online recruitment strategies is desirable. For a study on spectacle ownership in children and adolescents, we distributed a short online parent questionnaire across Germany. We employed five recruitment strategies, which included (a) recruiting schools and kindergartens via multistage cluster sampling to advertise the study, (b) advertising the study on a website for recruiting child and parent online study participants, (c) distributing the study within the researchers' personal and professional networks, (d) sending postal participation invitations to randomly selected families within the city of Dortmund, and (e) distribution of the questionnaire online in forums, Facebook groups, and via Instagram influencers. Here, we describe the strategies' methodology and evaluate them regarding data quality, recruitment success, demographic structure and representativeness, costs, and workload. We found large differences with regard to recruitment success and workload as well as the number of questionnaires acquired per working hour. The samples' age distribution was not representative of that in the German population for most strategies, while the opposite was true for gender distribution. Also, while there was some between-strategy variation regarding monetary costs, they were generally low for all strategies, and some did not involve any costs at all. We thoroughly discuss and compare the analyzed criteria across strategies and overall, in the hope that this might help to assess their suitability for other investigations. Overall, each strategy has specific advantages and disadvantages. Thus, the usefulness of each strategy depends on factors such as study aim and resources in the given situation.

2.2.1. Introduction

With the advancement of online research methodology (Germine et al., 2012; Kaduk et al., 2023; Reimers & Stewart, 2015; Semmelmann et al., 2017; Semmelmann & Weigelt, 2018), including online questionnaires becoming increasingly popular for data collection (Andrade, 2020), there is also a growing need for strategies to recruit participants for online studies. This need had become especially prominent during the Covid-19 pandemic, when online research was the only means of data collection at times.

When distributing online studies among potential participants, one needs to consider many aspects, which may vary in relevance depending on the kind of research conducted. For example, the need to try and minimize the risk of survey fraud (taking an online survey multiple times) or inattentive response behavior due to survey fatigue (Singh & Sagar, 2021) is potentially important in unsupervised online questionnaire studies, but not so much in studies in which the participant is virtually supervised by a researcher. Furthermore, while the participant recruitment process is sometimes reported on in detail (e.g., Arcia, 2014; Leighton et al., 2021; Pedersen et al., 2015), this is often not the case (both regarding in lab and online research).

If not communicated, specific knowledge regarding different recruitment strategies stays within the research teams using them. This is especially unfortunate for online research: Not only can aspects of the recruitment process influence the research outcome (see below), but relevant factors like the popularity of certain social media platforms or online tools can change quickly, and sharing experiences can help to stay up-to-date. Furthermore, research comparing various recruitment strategies for online studies has already demonstrated their sometimes large differences in various aspects (e.g., Antoun et al., 2016; Blumenberg et al., 2019; Dworkin et al., 2016). To give an example, Dworkin et al. (2016) compared targeted Facebook advertisements, e-mail Listservs, and the crowdworking website Amazon Mechanical Turk (MTurk) to recruit parents online. In online crowdworking (or crowdsourcing), employers put up tasks on a website, which can then be completed by registered workers. Upon successful completion, the workers receive a compensation. The website handles administrative aspects like suggesting tasks to workers and coordinating payment. Dworkin et al. (2016) discovered that MTurk achieved the most demographically diverse sample fast and cost-efficiently, while recruitment via Listservs led to a large, homogenous sample, and Facebook advertisements were unsuccessful in recruiting participants. However, other investigations have found Facebook advertisements to be an adequate and helpful recruitment strategy (Arcia, 2014; Pedersen et al., 2015). As demonstrated by these examples, recruitment strategies can differ considerably in their outcomes and between specific applications. Reporting experiences in participant

recruitment more thoroughly could help the research community to be aware of the various strategies' advantages and disadvantages and to generally improve participant recruitment.

For a study on spectacle ownership and myopia in children and adolescents, we distributed a short online questionnaire for parents across Germany via various participant recruitment strategies. The target group were families living in Germany with at least one child below the age of 18. Details of the study and the results pertaining to the content of the questionnaires are reported on in Study 3. For epidemiological research such as this study, online questionnaires are a promising tool for data collection, and they may even include specific advantages for research on sensitive topics, like a reduced susceptibility to social desirability (van Gelder et al., 2010). At the same time, it can be especially relevant for epidemiological studies to recruit a representative sample regarding the assessed aspects and factors that may influence these aspects – and online questionnaires might be problematic in this regard. While online research enables online recruitment, which may be helpful in recruiting more diverse and representative samples than those of typical experimental studies (Gosling et al., 2004; Gosling et al., 2010; Upadhyay & Lipkovich, 2020), the population to which an online questionnaire is distributed can often not be identified or adequately described, and biases in the sample are likely (Andrade, 2020) – which can restrict the informative value and generalizability of the data.

In light of the diverse recruitment strategies we employed in our study, we would like to share our insights into the recruitment process as well as relevant information and outcomes associated with each strategy. Therefore, we here present in detail the methodology of our recruitment strategies, and describe the respective outcomes in terms of the number of in- and excluded questionnaires and children reported on per recruitment strategy as well as estimated response rates. Furthermore, we assess the sample's age- and gender-wise distribution and representativeness overall and for each strategy. Lastly, we reflect upon our experiences with each strategy regarding monetary aspects and workload. We hope that this report will be helpful for researchers in assessing various recruitment strategies for online research, especially online questionnaire studies, with respect to relevant aspects for choosing methodology for own research.

2.2.2. Methods

2.2.2.1. Study Design

The study was comprised of two anonymous online questionnaires for parents regarding spectacle ownership of children and adolescents in Germany. The **short questionnaire** inquired about basic demographic information (gender, month and year of birth) as well as whether the children owned spectacles and – if they did – the reason (myopia,

hyperopia, other, unknown) for it. It only required information parents usually spontaneously know. The **long questionnaire** contained the same questions about demographic information and whether the children owned spectacles. If they did, participants were then asked to enter the spectacles' values and indicate the last time their fit was assessed by an eye health professional. If the children did not own spectacles, the long questionnaire inquired about potential sight problems, past eye health check-ups, school entry age as well as near work and outdoor time – with the latter three questions primarily included to control for questionnaire length. Regardless of whether or not the children owned spectacles, the final questions in the long questionnaire asked about their parents' ocular health. Thus, especially for parents of spectacle-owning children, completing the long questionnaire likely involved some research, e.g. checking the eyeglass prescription.

Participants were recruited for the short questionnaire. Upon completion, they were asked whether they would also like to participate in the long questionnaire. The short questionnaire took less than 1 minute to complete per child, and the long questionnaire took about 5 minutes per child. Both questionnaires could be filled in for up to five children.

For each recruitment strategy, we used a separate short questionnaire, with similar content in all questionnaires. We used the same long questionnaire for all recruitment strategies but one (see chapter 2.2.2.2), as analyzing the number of short questionnaire participants proceeding to fill in the long questionnaire was possible via referrer URL. The two long questionnaires did not differ in content.

Separate questionnaires following the short and long questionnaires were used to enable participants to enter a voucher raffle with an e-mail address, and in another questionnaire, following the long questionnaire only, they could enter contact and demographic information should they be interested in other studies in our lab. For reasons explained below, the raffle and future interest questionnaires were used in all but one strategy.

We created all questionnaires in LimeSurvey and used the option to save a cookie on the participant's device to prevent multiple participations (from the same device). Furthermore, participants could save the questionnaire amidst participation and return to it again later. Figure 2.5 presents an overview of the questionnaires and their connectedness. The different recruitment strategies and connections between the questionnaires will be explained in the following.

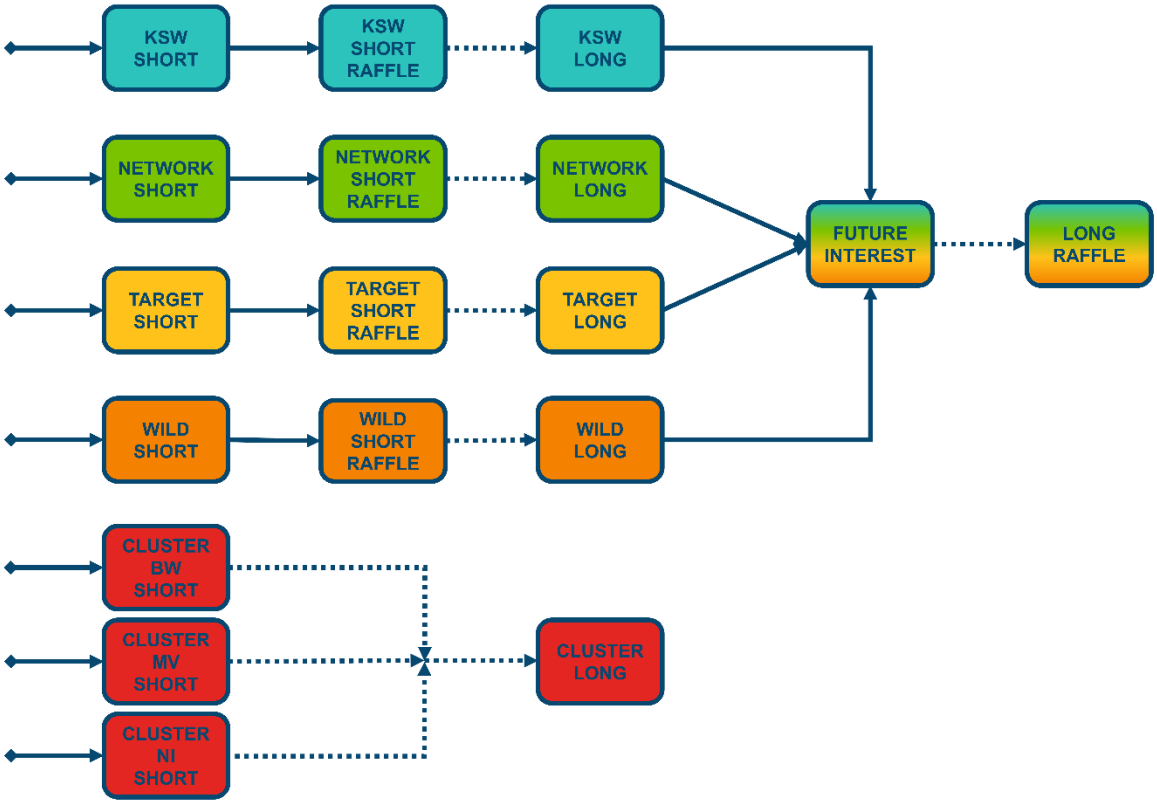

Figure 2.5. Overview of the questionnaires and how they are connected. Straight lines indicate an automatic redirection to the next questionnaire, while dotted lines indicate a redirection only after participants clicked on the respective link. KSW, NETWORK, TARGET, WILD and CLUSTER are the names of the recruitment strategies. BW, MV and NI indicate the German federal states of Baden-Wuerttemberg (Baden-Württemberg), Mecklenburg-Western Pomerania (Mecklenburg-Vorpommern) and Lower Saxony (Niedersachsen), respectively, which is where the questionnaires were distributed in the CLUSTER strategy (see below).

2.2.2.2. Participant Recruitment Strategies

In total, we used five recruitment strategies to distribute the questionnaires between September 2020 and January 2022.

The CLUSTER strategy included the questionnaire distribution in schools and daycare centers in Germany selected via *multistage cluster sampling*. First, we randomly selected two "old" (i.e., part of the Federal Republic of Germany prior German reunification) and one "new" (i.e., part of the German Democratic Republic prior German reunification) federal states. For this purpose, the three German federal city states were considered jointly with their surrounding federal states: Hamburg and Bremen were assigned to Lower Saxony and Berlin was assigned to Brandenburg. This led to eight "old" and five "new" federal states for the draw, which resulted in the selection of the federal states Baden-Wuerttemberg, Lower Saxony (plus Hamburg and Bremen) and Mecklenburg-Western Pomerania. Subsequently,

we randomly selected five counties within each of them. For each county, we created a daycare center list by randomizing all daycare centers listed in a directory (www.kitanetz.de). The directory does not necessarily include all daycare centers, but is one of the best options for a structured list containing as many as possible, as there are no official lists available. For schools, we used a list or directory listing public and private schools from the respective federal state's ministry concerned with education. We created and randomized one list for primary and one for secondary schools per county, whereby institutions including both types were categorized as secondary schools. For daycare centers and schools alike, we excluded institutions that only enroll children with special needs, but included those that enroll children with and without special needs. We then called the institutions in the order of our lists and asked them if they could either distribute advertisement for our study to parents (electronically or as a hand-out) or if they could put up a poster on the premises. If institutions agreed, they were called again about two weeks later to ask whether the distribution worked as discussed. In the selected federal states, one needs approval from the responsible authority – usually the respective ministries concerned with education – to conduct studies at schools. However, in Mecklenburg-Western Pomerania, our study was never assessed by the ministry, since they had requested clearance from the ministry of health, who did not have the resources due to the Covid-19 pandemic. Thus, schools were not recruited in Mecklenburg-Western Pomerania, but kindergartens were recruited in all three federal states. Furthermore, there was no voucher raffle in CLUSTER as including a monetary incentive for study participation was not allowed in some federal states when recruiting via public schools. Wanting to keep the methodology consistent within CLUSTER, we left the raffles out of this strategy completely.

The KSW strategy describes the participant recruitment via "Kinder schaffen Wissen" (kinderschaffenwissen.eva.mpg.de; "children create knowledge"), a website that was run by researchers in German-speaking countries to advertise studies to children and parents – similar to "Children Helping Science" (childrenhelpingscience.com) for English-speaking communities. The website was launched in November 2020 and the questionnaire was immediately posted. The possibility to enter a raffle was not advertised on the website, as advertising reimbursement was against its guidelines. Potential participants were informed about the raffle when they followed the link to the questionnaire.

The NETWORK strategy included all efforts to distribute the questionnaire in the researchers' personal and professional extended network – e.g., asking acquaintances to participate or to distribute it in their networks, posting it on private Instagram pages and in online groups, or contacting potential participants from our lab's database. Based on our assessment of each chosen distribution channel, information on the voucher raffle was either given or not when advertising the study. This recruitment strategy was coordinated and mainly carried out by a master's student as part of her thesis a) to avoid overlaps in

recruitment and b) to use a network of people that was not involved in initial questionnaire piloting.

For the TARGET strategy, we randomly chose six out of the 27 postal codes in the city of Dortmund, and requested names and addresses of everyone under the age of 18 living in the chosen areas from the population register. We then merged the information per postal code by grouping siblings together based on last names and addresses so that every family was only listed once. In two recruitment waves six weeks apart, we randomly chose 100 families per postal code and sent them a letter inviting them to participate, including information on the voucher raffle. Thus, a total of 1,200 letters – 600 per recruitment wave – were sent out to families.

In the WILD strategy, we distributed the questionnaire online. Specifically, we posted it in online forums as well as Facebook groups and asked Instagram influencers to share it with their followers. Apart from few exceptions, we only advertised the questionnaire in groups and online forums where we expected most members and visitors to be parents. In the few exceptions, we e.g. posted study advertisement in Facebook groups for survey participants, making it very clear in the caption that this post was only relevant for families living in Germany and did not advertise the associated voucher raffle in the caption – or not at all, depending on the situation. On Instagram, we only approached influencers addressing topics like children or parenthood.

2.2.2.3. Data Analysis

The data presented here is mostly descriptive in nature, and we do not have the same information available for all recruitment strategies. Yet, to give a realistic overview of our recruitment efforts and outcomes, we present the data as comprehensively as possible. If not otherwise specified, the number of included instead of completed questionnaires is reported and used for calculations, since both are very similar (see chapter 2.2.3).

Firstly, data quality is of course important for any investigation. Unfortunately, we cannot comprehensively assess this with the available data (see chapter 2.2.4). However, one potentially relevant aspect of data quality for questionnaire studies that we can examine is the number of questionnaires that had to be excluded due to data being unreasonable (e.g., "5" given as year of birth) or not meeting the inclusion criteria (e.g., "child" reported on is over 18 years old). Thus, we report the number and percentage (based on completed questionnaires) of excluded questionnaires per recruitment strategy for both the short and long questionnaire.

For each recruitment strategy, we then report on the number of questionnaires – which equals the number of participants (i.e., parents), assuming each participant only completed one questionnaire – as well as the number of children for which data was reported for both short and long questionnaire. We also present the percentage of short questionnaire participants per strategy who completed the long questionnaire as well. Since the short questionnaire was the one we advertised and based most of our analyses regarding epidemiological data on (see Study 3), only the short questionnaire will be considered in the following analyses.

Next, we describe estimates for the number of people potentially reached by the recruitment strategies to approximate response rates. Note that the available data and degrees of certainty differ between strategies, so the data is not directly comparable between them. For some strategies, both the number of potentially reached participants as well as children to be reported on is available. For others, information is only available for one aspect or even none. Where possible, we calculate the percentage of potential participants who actually participated and the percentage of potentially reached children on whom we have data. We call the former participation rate and the latter child data rate, respectively.

To assess sample representativeness, we then present the demographic structure of the children per recruitment strategy with regard to gender and age, and compare the distribution of both aspects to that in Germany (Statistisches Bundesamt, 2023a, 2023c, 2023d) with Chi-Square Goodness of Fit tests. Age was assessed in age groups of 3 years each, as this is how the epidemiological data was presented and analyzed (see Study 3). Gender was assessed with regard to females and males only, because while our study included non-binary children, the data for the German population so far only includes the genders female and male.

Monetary aspects and workload are important practical issues when planning a study. We therefore describe our costs (excluding working hours) per recruitment strategy. Lastly, we also indicate the workload by describing the amount and type of work per strategy and providing an estimation regarding the number of working hours we spent per strategy. Since we were not able to completely track working hours, it is important to keep in mind that the numbers given for working hours are broad estimates only. Finally, we calculate a questionnaire-workload ratio for each strategy by dividing the number of included questionnaires by working hours to estimate the number of included questionnaires per hour of work for each strategy.

2.2.3. Results

2.2.3.1. Data Quality

To develop a sense of the data quality, we analyzed the number of excluded questionnaires per strategy. Only 16 (1.5%) short and 4 (1.8%) long questionnaires had to be excluded overall. The excluded short questionnaires are distributed among the strategies as follows: CLUSTER – 1 (0.5%), NETWORK – 13 (2.5%), TARGET – 2 (1.4%). Two long questionnaires were excluded from both NETWORK (2.4%) and TARGET (3.9%), respectively. Reasons for exclusion mostly were the people reported on being over 17 years old or an incorrectly given year of birth. Either of this was the case for all excluded short and two excluded long questionnaires. One further long questionnaire was excluded due to implausible spectacle specifications, and one due to a mismatch between a child's age and school entry age. Generally, we applied rather strict exclusion criteria. For example, questionnaires were excluded if a year of birth had not been given in the correct format – even in cases where one might have reasonably assumed the correct year (e.g., "207" for "2007" or "05" for "2005"). Furthermore, if one child within a questionnaire had to be excluded, we completely excluded the questionnaire. There does not seem to be a distinct pattern across recruitment strategies with regard to excluded questionnaires. Yet, due to the exclusion rates being low in general, this finding is not necessarily very informative. The low exclusion rates could (partly) be due to the fact that our questionnaire was easy to answer – either with real or real-looking fake values, the implications of which will be considered in chapter 2.2.4.

2.2.3.2. Number of Questionnaires and Children

The number of included questionnaires (i.e., participants) and children overall and per recruitment strategy for both questionnaires can be seen in Table 2.7.

It is well apparent that most short questionnaires by far were obtained via NETWORK, and the second-most via CLUSTER. Only a few questionnaires stem from KSW. Interestingly, while questionnaires from NETWORK still constitute the largest number for the long questionnaire, the difference to the other strategies is not as considerable anymore. This is also evident in the percentage of short questionnaire participants who completed the long questionnaire: Overall, 20.4% of short questionnaire participants did so, but this number differs between strategies. For CLUSTER, only 8.7% of participants completed the long questionnaire and for NETWORK, only 16.4% did. For WILD, this number is 23.6%, and for TARGET, it is 35.8%. KSW exhibited the highest respective percentage, namely 42.7%.

Table 2.7

Number of Included Questionnaires and Children per Recruitment Strategy

	short questionnaire					
	overall	**CLUSTER**	**KSW**	**NETWORK**	**TARGET**	**WILD**
questionnaires	1,082	206	82	500	137	157
children	1,747	340	140	821	215	231
children/questionnaire	1.61	1.65	1.71	1.64	1.57	1.47
	long questionnaire					
	overall	**CLUSTER**	**KSW**	**NETWORK**	**TARGET**	**WILD**
questionnaires	221	18	35	82	49	37
children	341	26	56	144	66	49
children/questionnaire	1.54	1.44	1.6	1.76	1.35	1.32

Lastly, the number of children per questionnaire is relatively similar between recruitment strategies, with a bit more variation for the long questionnaire – which is unsurprising given the smaller number of long than short questionnaires.

2.2.3.3. Number of Potential Participants and Children

The information regarding the number of potential participants or children reported on differs between strategies, leading to varying informative values and limitations. This will be explained in more detail within the respective sections.

For CLUSTER, some assumptions needed to be made to estimate the number of potential participants and children reported on, so the reported numbers and rates should be seen as broad approximations. First, we calculated the total number of children visiting all educational institutions that advertised our study. One school included grades 11-13, in which some students would be 18 or more years old. For this school, we estimated the number of students per grade (total number of students/number of grades), and excluded half of the students in grades 11-13, which led to an exclusion of 92 students. With this, the estimated total number of underage children visiting all institutions was 9,062. The CLUSTER short questionnaire was completed for 340 children, corresponding to 3.8% of said children. However, the actual number of potentially reached children should be higher due to siblings that do not visit the same institutions. This can only be approximated with multiple assumptions: On average, 1.83 underage children lived in a family in Germany in 2022

(Statistisches Bundesamt, 2023b).[2] Since siblings close in age often visit the same institutions, we approximated 1.5 underage children per family who do not, and used this number to estimate 13,593 (9,062 x 1.5) potentially reached children via CLUSTER.[3] With this estimation, the child data rate (i.e., the percentage of potentially reached children on whom we have data) for CLUSTER is ca. 2.5%. Using the above-mentioned 1.83 underage children per family, we then estimated the potentially reached families – as a proxy for potential participants – as 7,427 (13,593 / 1.83). With 206 included CLUSTER short questionnaires, this sets the participation rate (i.e., the percentage of potential participants who actually participated) for CLUSTER at ca. 2.8%.

For KSW, it is not possible to estimate potential participants or children, since there is no information about how many people were informed about or visited the website "Kinder schaffen Wissen".

Likewise, we cannot provide sensible overall estimations for NETWORK. Several factors play a role in this. For example, many networks in which we distributed the study, contain an unknown number of people and/or parents. Furthermore, a lot of recruitment was via word of mouth, and it would have been impossible to track all this. To give an impression about the order of magnitude of directly approached people with regard to NETWORK, we present the larger recruitment efforts – i.e., where we successfully advertised our study – together with an estimate of how many people it potentially reached in Table 2.8. Depending on the situation, this number may either indicate parents (i.e., potential participants) or children (i.e., potential children to be reported on that we know of) or people in general (i.e., including only some potential participants).

[2] To calculate this number, families with five or more underage children were counted as families with five underage children as more accurate data was not available.

[3] In calculating this, we did not account for the excluded adult students potentially having underage siblings at other institutions for which the questionnaire might be completed – but as the numbers are rather broadly approximated, and we only estimated 92 students to be 18 years or older, we considered this to be negligible.

Table 2.8

Overview of Larger NETWORK Recruitment Efforts

type of recruitment	people potentially reached	comments
posting on a personal Instagram account	1,865 followers	presumably only a small percentage of parents among the followers
distribution in a secondary school (Gymnasium)	800 students	
posting in a chat group of a town district	359 members	mostly younger people, presumably only a small percentage of parents
e-mails to families that are interested in participating in research in our lab	262 families	287 mails sent, 25 came back to sender
posting in a Facebook group of a town district	200 members	not all members were parents
distribution in a student chat group	157 members	all members were students, probably only a few parents

Apart from the recruiting indicated in Table 2.8, our study was advertised via multiple e-mail distribution lists and chat groups. The number of recipients probably varies between 10 and about 100, but is hard to estimate, as is the number of potential participants within them. Some groups and mailing lists were comprised solely of parents (e.g., parent WhatsApp groups), others only partly (e.g., academic network e-mail distribution lists). Lastly, members of the lab advertised the study within their personal network. Considering the numbers of potentially reached people and comments in Table 2.8 shows that even if, say, 500 further potential participants were reached, the number of potential participants or children is nowhere near as high as in CLUSTER. As the NETWORK strategy obtained more than twice as many completed short questionnaires than CLUSTER, with data for more than twice as many children, both participation and child data rate are considerably higher for NETWORK than CLUSTER.

Within TARGET, 22 (19) of the 600 letters from the first (second) recruitment wave were returned to sender. Thus, 578 (581) potential participants were reached in the first (second) wave, as were – based on information in the population register – 915 (913) children. With 137 included short questionnaires reporting on 215 children for TARGET, the reported numbers set both the TARGET participation rate and child data rate at 11.8%. Regarding the latter, one should note that some potential participants might have had more children to report on than reflected in the number of children – for example, if they had more underage

children registered under a different address or if children with different last names lived in the same family, since we grouped siblings together based on last names and addresses.

For WILD – like NETWORK – we cannot estimate an overall number for potential participants or children reached. Depending on the advertisement location, the following information may be available: a) number of views of the forum posting, b) number of Facebook group members, and c) number of followers of the respective Instagram influencer. Importantly, while a) indicates how many people saw the advertisement, this is not the case for b) and c), as there may be inactive Facebook group members or Instagram followers. It is therefore impossible to estimate how many potential participants or even people overall were reached. However, to give an impression about the order of magnitude, an overview of our WILD online postings along with the number of potentially reached people as described in a) – c) is presented in Table 2.9.

Table 2.9

Overview of WILD Online Postings

topic	people potentially reached	comments
online forums		
questions on topics like housekeeping	1,047 views	not specifically for parents
parenting questions	1,006 views	
online forum for parents	1,000 views	
self-help	983 views	not specifically for parents
raising children	829 views	
raising children	673 views	
buying & selling children's clothing	n/a	
desire for children, pregnancy, babies	n/a	
online forum for mothers	n/a	
online forum for parents	n/a	
parenting questions	n/a	
pregnancy, children, family	n/a	
women's lifestyle, fashion, etc.	n/a	not specifically for parents

Table 2.9 – Continued

Overview of WILD Online Postings

Facebook groups		
student surveys	14,300 members	not specifically for parents
creative child activities	7,872 members	
surveys & participants	6,200 members	not specifically for parents
surveys & thesis questions	4,500 members	not specifically for parents
activities for children	3,800 members	
self-help for parents/mothers	3,763 members	
cooking for families	3,069 members	
group for parents	2,746 members	
surveys & participants	2,300 members	not specifically for parents
town district activities	1,200 members	not specifically for parents
parent group about inclusion	464 members	
Instagram influencers		
everyday life as a mother	18,200 followers	
everyday life as a mother	15,900 followers	
everyday life as a father	11,200 followers	
everyday life as a mother	11,100 followers	
everyday life as a mother	2,572 followers	
sleep coaching for babies & toddlers	1,918 followers	
family life	1,321 followers	
everyday life as a mother	473 followers	

Note. In online forums that were not specifically for parents/families, the posting was made in a thread or sub-forum for online studies and clearly marked as being for parents only. The latter was also done in case of Facebook groups that did not target parents/families.

2.2.3.4. Children's Demographic Structure

Table 2.10 presents the number of included children from the short questionnaire per age group and gender overall and for each recruitment strategy.

Table 2.10

Number of Included Children per Age Group and Gender per Recruitment Strategy

	recruitment strategy					
age group	**overall**	**CLUSTER**	**KSW**	**NETWORK**	**TARGET**	**WILD**
overall	1747	340	140	821	215	231
	858 (f)	147 (f)	65 (f)	438 (f)	101 (f)	107 (f)
	888 (m)	193 (m)	75 (m)	383 (m)	114 (m)	123 (m)
0-2 years	217	37	23	57	36	64
	104 (f)	18 (f)	8 (f)	28 (f)	20 (f)	30 (f)
	113 (m)	19 (m)	15 (m)	29 (m)	16 (m)	34 (m)
3-5 years	305	92	34	90	39	50
	130 (f)	36 (f)	19 (f)	41 (f)	16 (f)	18 (f)
	175 (m)	56 (m)	15 (m)	49 (m)	23 (m)	32 (m)
6-8 years	320	94	32	109	46	39
	154 (f)	40 (f)	16 (f)	60 (f)	21 (f)	17 (f)
	166 (m)	54 (m)	16 (m)	49 (m)	25 (m)	22 (m)
9-11 years	301	46	24	165	31	35
	146 (f)	15 (f)	10 (f)	87 (f)	14 (f)	20 (f)
	155 (m)	31 (m)	14 (m)	78 (m)	17 (m)	15 (m)
12-14 years	355	48	18	228	33	28
	183 (f)	26 (f)	7 (f)	120 (f)	15 (f)	15 (f)
	172 (m)	22 (m)	11 (m)	108 (m)	18 (m)	13 (m)
15-17 years	249	23	9	172	30	15
	141 (f)	12 (f)	5 (f)	102 (f)	15 (f)	7 (f)
	107 (m)	11 (m)	4 (m)	70 (m)	15 (m)	7 (m)

Note. The first number per cell – shaded in gray – indicates the number of children of all genders, including non-binary children. (f) indicates the number of females, (m) the number of males in each subsample.

With regard to gender, in the total sample, more males than females were included in the analyses for the younger age groups up to and including 9-11 years. For the two oldest age groups, this pattern was reversed. From all strategies but NETWORK, there is again more data for males than females overall, with the opposite being true for NETWORK.

The largest age group overall is that of 12-14-year-olds. Fewest children were in the youngest age group (0-2 years), followed by the oldest one (15-17 years). Considering the recruitment strategies separately, it is interesting to note that for NETWORK, more children stem from the older than the younger age groups, while the opposite is true for CLUSTER and WILD. For both KSW and TARGET, the age groups are relatively balanced, except that in KSW, the number of children in the two oldest age groups is somewhat reduced.

2.2.3.5. Representativeness of Children's Demographic Structure

We assessed the representativeness of the children's demographic structure overall and per recruitment strategy by comparing the age (in age groups of 3 years) and gender distribution within each (sub)sample to that of Germany. Regarding age, the number of people per age group of our study in the German population is shown in Table 2.11. Holm-corrected (Holm, 1979) Chi-Squared Goodness of Fit tests revealed a significant deviance of the (sub)samples' age distributions from that in the German population for the overall sample and all strategies but TARGET (TARGET: X^2 (5, N = 215) = 3.536, p = .618, all other strategies & overall sample: $p < .05$). For gender, the situation is different: Here, the distribution in the (sub)samples was significantly different from that of the German population (ca. 7,314,393 males and 6,890,767 females in December 2022; calculated from: Statistisches Bundesamt, 2023c, 2023d) for NETWORK (X^2 (1, N = 821) = 7.702, p = .033), but not for any other strategy or the overall sample (all ps > .05).

Table 2.11

People per Age Group in the German Population in December 2022

0-2 years	3-5 years	6-8 years	9-11 years	12-14 years	15-17 years
2,354,778	2,466,776	2,458,992	2,317,443	2,330,988	2,322,746

Note. Calculated from data in Statistisches Bundesamt (2023a).

2.2.3.6. Monetary Aspects

Monetary aspects – excluding working hours – are of a rather limited importance for most of our recruitment strategies. KSW and WILD did not include any costs. For CLUSTER, the only expense was 101€ to obtain a list of schools from the statistical office of one federal state. All other institutions were obtained from databases free of charge. There were no further costs for CLUSTER, the costs for this strategy thus amounting to 0.30€ per child included in the analysis. We did offer the institutions to send them material via post if they

opted to advertise the study non-electronically, which would have included further costs. However, all respective institutions printed the material themselves. NETWORK included no costs apart from very sporadic printing and sending study information via post. As the vast majority of NETWORK recruiting was done electronically, this accumulated to expenses of 15€ at maximum, thereby costing 0.02€ per included child at most. Lastly, printing and sending the letters to the 1,200 families within TARGET cost ca. 440€, and thus 2.05€ per included child.

Additionally, we raffled vouchers with a total value of 600€ to motivate participation. However, this is not directly related to the recruitment process and can theoretically be omitted, or vouchers of lower value can be used.

2.2.3.7. Workload

To give an indication about the type and amount of work researchers can expect per recruitment strategy, both will be described in the following, as well as how workload and recruitment success related to one another.

CLUSTER entailed a lot of organization, especially to obtain permission for recruitment in schools and to create the various institutions lists, which we estimate at about 25 hours of work. Furthermore, calling the institutions and sending them information via e-mail alone entailed the most workload by far within all strategies, easily accumulating to about 100 hours of work, leading to an estimation of 125 hours of work for CLUSTER recruiting. Overall, we tried to contact 275 institutions via telephone. Despite trying several times, we were unable to reach 66 of those institutions. Thus, 219 institutions were successfully contacted, of which 79 participated – i.e., 28.7% of the institutions we tried to contact and 36.1% of those we successfully contacted. Prior declining or agreeing to our request, most institutions were contacted multiple times due to difficulty in reaching the relevant personnel and the common practice of internal discussion of our request before responding to it. The institutions who agreed to advertise the study also received a follow-up call two weeks later. Generally, coordinating the CLUSTER recruitment constituted a significant portion of the overall recruitment workload, extending beyond the actual hours spent on contacting institutions, mostly because the availability of institutional heads necessitated recruitment efforts to be dispersed rather than conducted continuously for an extended duration.

In contrast, KSW entailed minimal workload, as it only needed to be posted on the website once after creating an account for the lab. We estimate KSW recruitment to not have taken longer than 2 hours.

NETWORK recruiting encompassed making lists of potential recruiting opportunities, writing e-mails and distributing information in the respective networks as well as asking others to do so and providing them with materials. Furthermore, the people who were asked to distribute the information in their networks had some workload as well, but as the advertisment texts were usually given to them, their workload was limited to a few minutes. With this, we estimate about 14 hours of work for NETWORK recruiting, including the work from people other than the primary researcher(s).

For TARGET, recruiting included randomizing the postal codes, obtaining the lists from the population register, writing a script to merge families within the lists and randomly extracting those to send letters to as well as writing and stamping the letters. Theoretically, printing and sending the letters would also be workload, but since this was payed for and carried out externally, it is not included in the researcher workload. The latter accumulated to ca. 11.5 hours of work.

WILD – like NETWORK – included some time of researching recruiting opportunities and preparing materials. Beyond that, asking permission to distribute the information as well as regularly checking the postings for updates and questions took more time. In total, we approximate about 46 hours of work for WILD. We tried posting the study in 20 online forums, and succeeded in 13 (65%). With regard to Facebook, we tried posting in 22 groups, and succeeded in 11 (50%). Note that these high rates of successful posting were a result of researching many more forums and groups, and if and how it was allowed to post study advertisements. Had we not done that, the rate of successful postings would most likely be considerably lower, as it is for Instagram: Here, we contacted 104 influencers, of which 8 (7.7%) posted our study advertisement. Most of the contacted influencers did not reply.

Despite only being able to provide broad estimations regarding the working hours per recruitment strategy, the following can be said: In our study, CLUSTER involved the most extensive recruitment effort, followed by WILD, NETWORK, TARGET, and KSW. While KSW only took minimal effort, both NETWORK and TARGET still required several hours of work – yet, they were considerably less labor-intensive than both CLUSTER and WILD. NETWORK and TARGET included a comparable amount of work for the primary researcher(s), but NETWORK involved more coordination and also created workload for others, and we thus estimated it to be more laborious.

Lastly, we calculated approximate questionnaire-workload ratios (i.e., number of included questionnaires per hour of work) for each strategy, which are as follows:

- CLUSTER: 1.6
- KSW: 41.0
- NETWORK: 35.7
- TARGET: 11.9
- WILD: 3.4

As can be seen, the strategies differ vastly in their questionnaire-workload ratios, with CLUSTER having the worst and KSW the best. The association between workload and questionnaire numbers will be addressed more in chapter 2.2.4.

2.2.4. Discussion

In this report, we describe our efforts and outcomes in distributing a short online parent questionnaire via five recruitment strategies. Upon completing the short questionnaire, participants were invited to also participate in a longer one. As for the Results sections, the aspects discussed in the following relate to the short questionnaire, if not otherwise specified. The recruitment strategies included (a) recruiting schools and kindergartens via *multistage cluster sampling* to advertise the study (CLUSTER), (b) advertising the study on a website for the recruitment of child and parent online study participants (KSW), (c) distributing the study within the researchers' personals and professional networks (NETWORK), (d) sending postal invitations to participate in the study to randomly chosen families within the city of Dortmund (TARGET), and (e) distributing the questionnaire online in forums, Facebook groups, and via Instagram influencers (WILD). Upon describing each strategy's methodology, we analyzed them with regard to data quality, recruitment success (number of included questionnaires and children reported on as well as number of potential participants/children and response rates), demographic structure and representativeness, monetary aspects and workload. In the following, we will discuss and compare these criteria across strategies. Due to a large topical overlap, workload will be considered together with recruitment success.

2.2.4.1. Data Quality

Data quality could only be analyzed superficially by checking the number of excluded questionnaires, and only very few questionnaires had to be excluded from analysis. While it is great that exclusion rates due to unreasonable data or not meeting inclusion criteria are uniformly low, faking realistic-looking answers in our questionnaire would be rather easy. Thus, we can neither detect nor exclude questionnaires with false but realistic-looking data, and are thus also unable to estimate if and to what extent they exist.

If one considers a questionnaire at risk for low data quality due to response biases (incorrect answering for various reasons; Wetzel et al., 2016), trying to ascertain more control over this aspect may be helpful. In-questionnaire examples for better controlling data quality are including questions to measure the social desirability bias, e.g. from (versions of) the Marlowe-Crowne Social Desirability Scale (Crowne & Marlowe, 1960), or attention-check questions to test whether respondents actually pay attention (Dworkin et al., 2016). Being more restrictive in recruitment might also enhance data quality, e.g. by having interested individuals contact the researchers to receive a code for participation. An approach like this may be useful with regard to survey fraud (participating more than once; Singh & Sagar, 2021) or participating despite not fitting the inclusion criteria, deliberately giving wrong answers – both probably especially relevant in case of guaranteed compensation. However, it also poses a large hurdle for potential participants – which, in turn, likely makes a guaranteed compensation necessary to receive an adequate sample size.

One measure we took to minimize survey fraud was setting a cookie on the participant's device to prevent multiple participations – although participating again would still have been possible from another device or after deleting cookies, so this would not have prevented especially technically adept individuals from doing so. We also checked whether e-mail addresses were used in the voucher raffle more than once, which was not the case. While this is a hint that participants did not complete the questionnaires multiple times for a higher chance in the raffle, it obviously does not rule it out either, as they may have used different e-mail addresses.

We did not employ any other of the described techniques because for one, due to our questionnaires being neither long nor of a sensitive nature, we did not assume inattentiveness or social desirability bias to be problematic. Furthermore, with the only compensation being the opportunity to participate in a voucher raffle (which was not even advertised everywhere), the risk of people participating multiple times or with fake answers to gain the compensation was probably not very high either. Especially the latter risk is probably much more relevant with guaranteed compensation. One way to reduce the risk of survey fraud while still rewarding each participation may be donating money to a charity per participation instead of giving it to the participant (Singh & Sagar, 2021). Overall, however,

our assumptions regarding the likelihood of low data quality are speculative, as it is e.g. possible that we underestimate the motivation of people to participate using fake data to enter a voucher raffle.

2.2.4.2. Recruitment Success and Workload

Despite large(r) recruitment efforts in other strategies, NETWORK yielded the most questionnaires and highest number of children reported on by far. NETWORK also revealed a very high questionnaire-workload ratio (i.e., number of included questionnaires per hour of work), second only to KSW. Additionally, we assume a much higher participation rate (i.e., percentage of potential participants who actually participated) and child data rate (i.e., percentage of potentially reached children on whom we have data) for NETWORK than e.g. for CLUSTER, which involved the largest recruitment workload. This discrepancy may be attributed to the likelihood that individuals familiar with the researchers were more inclined to contribute, possibly viewing it as a favor or expressing confidence in the integrity of the researchers. This inclination is especially relevant as the only compensation for participating was a voucher raffle. Guaranteed compensation might have made non-acquaintances – i.e., potential participants from other strategies than NETWORK – more inclined to participate. Yet, guaranteed compensation in online research poses other challenges, as discussed below.

In general, the order of workload corresponds to the number of included questionnaires per strategy – with the exception of NETWORK obtaining the most questionnaires by far while not involving the highest workload. Furthermore, while the order aligns appropriately for CLUSTER and TARGET, with both higher in CLUSTER, the magnitude of the workload difference vastly exceeds that of the questionnaire numbers, with TARGET yielding a substantially better questionnaire-workload ratio than CLUSTER. A similar trend, albeit to a lesser extent, is observed in the comparison between CLUSTER and WILD. CLUSTER being the only strategy without the opportunity to enter a voucher raffle likely reduced its recruitment success compared to the other strategies both in terms of response rates and questionnaire-workload ratio. TARGET recruitment having taken place in the same city of TU Dortmund University, on the other hand, may have helped its participation rates compared to other strategies (except NETWORK): People contacted via TARGET might feel connected to the university due to personal experiences or regional reference, and might thus have been more inclined to participate than people who did not really know the university. Lastly, KSW generated the fewest questionnaires, but it also only included minimal workload, thus yielding an extremely favorable questionnaire-workload ratio.

It is intriguing that NETWORK, despite its success in recruiting for the short questionnaire, had the second-smallest percentage of participants also completing the long

one (16.4%). This suggests that while many NETWORK participants may have filled in the short questionnaire as a favor, their interest in the study's topic might not have extended to the level of commitment required for the long questionnaire. Furthermore, the high rate of participants also completing the long questionnaire for TARGET (35.8%) and KSW (42.7%) is noteworthy. This might be a result of interest and convenience: Visitors to the KSW website were likely already interested in participating in studies and may have assumed that such studies would require more time than the short questionnaire did. Additionally, they were likely at home when browsing the website, providing them with the time and resources needed for the extensive information required for the long questionnaire. The latter may also apply to TARGET. Since families received invitations via letters, parents could choose when to complete the questionnaire, and they were presumably also at home during the process. Lastly, CLUSTER exhibited the lowest percentage of participants also completing the long questionnaire (8.7%). The lack of compensation in CLUSTER may again have played a role: While the short questionnaire can be answered quickly, in the absence of any incentive, participants might not have been motivated enough for the long one.

2.2.4.3. Demographic Structure and Representativeness of the Sample(s)

The observed variations in age distribution among the recruitment strategies are rather unsurprising. For one, NETWORK mostly includes older children, likely a result of individuals within the researchers' networks predominantly having children in middle childhood or older. Additionally, the recruitment of one acquainted secondary school led to a notable influx of questionnaires for older age groups. Meanwhile, CLUSTER exhibits a higher proportion of younger children. This can likely be attributed to the exclusive recruitment of kindergartens in one federal state, and a general tendency of kindergartens and primary schools to be more open to distributing questionnaires than secondary schools. WILD also demonstrates a higher representation of younger children, probably due to the demographic characteristics of parents who are active online. Especially social media users are generally younger, and thus more likely to have younger children as well: In both Facebook and Instagram users, the most represented age groups worldwide were 18-24 years and 25-34 years (We Are Social et al., 2023a, 2023b). New parents seeking advice in online forums, often targeted at parents with babies or toddlers, may also contribute to the higher prevalence of younger children in the WILD dataset. For KSW, the age groups are mostly balanced, except for a somewhat reduced number in the two oldest age groups. The KSW website was largely advertised as including studies to do with children. It is thus possible – albeit speculative – that the slight age group imbalance might be attributed to adolescents being less interested in participating than younger children, and thus their parents being less encouraged to browse the website. Finally, TARGET exhibits a fairly even distribution of

children across age groups, likely attributable to the fact that the letter-based recruitment does not inherently lend itself to age-related preferences. This results pattern is also represented in the analysis of age-related sample representativeness: Only the TARGET age distribution does not differ significantly from that in the general German population, where the number of people aged 0-17 years is relatively balanced (between 737,780 and 838,586 individuals per year of age; Statistisches Bundesamt, 2023a) as compared to other ages (Statistisches Bundesamt, 2023a). One should also assess the potential influence of the investigation's topic on the sample demographics. For example, the comparison of epidemiology-related results from the present study with other studies indicates an overrepresentation of participants with spectacle-owning children in our study, which may be explained by higher thematic interest (see Study 3). Furthermore, refractive errors are generally more prevalent in older than younger children. It may therefore be possible that parents of older children were more likely to participate than those of younger one due to interest in the topic. However, the age structure within our strategies' subsamples rather indicate that strategy-related aspects likely primarily influenced the age distribution. If it is important to sample an age structure mirroring that in the population, these aspects need consideration.

The gender distribution was more balanced between strategies, with more males than females in the total sample and most strategies individually – except for NETWORK, where the opposite was true. Likewise, only the NETWORK gender distribution differs significantly from that of the German population, which also includes more underage males (ca. 7,314,393) than females (ca. 6,890,767; calculated from: Statistisches Bundesamt, 2023c, 2023d). Since for most strategies, there is no apparent strategy-related reason as to why they would favor participation of parents having children of a specific gender, it appears logical for the strategies' gender distribution to be similar to each other and the German population. However, it is again imaginable that thematic interest may have had implications for the sample demographics: As mentioned above, our data may include an overrepresentation of participants with spectacle-owning children (see Study 3). Furthermore, myopia was the most common reason for spectacle wear in our data (see Study 3), and is also more prevalent in girls than boys starting middle childhood (Rudnicka et al., 2016). Thus, an increased likelihood of participation among parents of girls compared to boys is theoretically conceivable. However, this does not seem to have much distorted the gender distribution in the data, since only NETWORK exhibits a disproportionally high number of females. Strategy-related reasons might have played a role in this, as there might have been more NETWORK recruitment in locations with more parents of girls than boys (e.g., a WhatsApp group of riding stables). However, this is very speculative and even if there was this imbalance in a few locations, it should not have exerted a large influence, since the majority of recruiting happened in locations where such biases would not be expected. In general, despite the

thoughts with regard to NETWORK being speculative and even though the potential thematic reason for gender distribution imbalances does not appear to have had a major influence on our data, such considerations are important for recruitment and data evaluation.

The importance of sample representativeness in these and other factors is of course based on the nature of the investigation. As discussed before, representativeness of relevant factors can be crucial in epidemiological studies. Our results demonstrate that even for relatively basic demographic factors, achieving representativeness can be challenging when recruiting for online studies. Moreover, our study did not include aspects like educational or socioeconomic status (SES), for which it is likely even more complicated to recruit a representative sample than for gender and age. On the other hand, recruiting diverse, representative samples is a well-known problem in in-lab research as well (Gosling et al., 2010; Henrich et al., 2010), and online studies may even be helpful to achieve diverse samples (Dworkin et al., 2016; Gosling et al., 2004; Gosling et al., 2010; Upadhyay & Lipkovich, 2020).

In our study, variables such as educational status or SES would have been interesting to include due to their associations with myopia (Foster & Jiang, 2014; K. M. Williams, Bertelsen, et al., 2015). For example, we suspect an oversampling of participants with high(er) educational status, especially in NETWORK and KSW (see Study 3). Participation biases with regard to educational status have been found in health survey studies before (e.g., Berra et al., 2007; Klijs et al., 2015), and also in epidemiological research on myopia. For example, undersampling of participants with low educational status is reported in the German Health Interview and Examination Survey for Children and Adolescents (KiGGS), amongst others also presenting data on myopia prevalence (Hoffmann et al., 2018; Schuster et al., 2020).

Overall, it is necessary in epidemiological research to assess and possibly control distribution and representativeness of relevant demographic factors. One can try to counteract participation biases in recruitment. For our strategies, this might e.g. have included oversampling schools in areas with a high presence of the characteristic for which undersampling is expected (CLUSTER) or postal codes of respective areas (TARGET). The latter strategy was e.g. applied for children and adolescents without German citizenship in the KiGGS study (Hoffmann et al., 2018). If one was unsuccessful in recruiting a representative sample, but needs one, one might consider taking this into account in data analysis. For example, one might adjust the sample by randomly deleting participants with the oversampled expression of the relevant characteristic. However, this of course comes with the drawback of reducing sample size and thus losing data. Another possibility is weighing the participants with regard to said characteristic, as has also been done in the KiGGS study regarding several aspects (Hoffmann et al., 2018; Schuster et al., 2020). We did not apply such strategies, as assessing the usefulness of online questionnaires to gain representative samples via multiple recruitment strategies and to estimate myopia

prevalence data was one aim of the study. And while representativeness regarding, for example, age groups is not given in our sample, and we cannot assess other potentially interesting factors like educational status or SES, the study's results suggest that the data may still be suitable for capturing data to monitor myopia prevalence (within the constraints of what is possible for questionnaires; see Study 3).

2.2.4.4. Monetary Aspects

Most of our recruitment strategies did not involve high costs: KSW and WILD did not include any, and NETWORK only very little for the occasional print-out. In CLUSTER, we did pay for a list of schools, but it would have also been possible to instead put in more working hours to research the schools manually. The only exception to all the strategies being very cost-effective is TARGET. With estimated costs of 440€ overall and 2.05€ per child included in the analysis, this strategy was the most expensive by far. Generally, monetary aspects may be more important for other strategies that e.g. involve a guaranteed compensation or paying for advertisements (see chapter 2.2.4.6).

In our study, the voucher raffle of course also included costs. Using a raffle as an incentive can theoretically be omitted – although it is surely easier to ensure sufficient participation if there is some incentive other than personal motivation. However, not only a missing incentive, but also one too high may be problematic in online research, as monetary incentives generally increase the risk of survey fraud (Singh & Sagar, 2021).

2.2.4.5. General Assessment of the Recruitment Strategies

Here, each strategies' most relevant aspects will be summarized and discussed comprehensively.

CLUSTER achieved the second-largest number of questionnaires, but with the highest workload by far, exhibiting the least favorable questionnaire-workload ratio with only 1.6 included questionnaires per hour of work. Since we suspect the absence of voucher raffles in CLUSTER to have reduced participation motivation, it is hard to estimate how the strategies' relative success compared to CLUSTER would have been had raffles been included in the latter. From our experience, it is common for incentives to be forbidden when recruiting via schools. Like for most strategies, the CLUSTER subsample was not representative of the German population in terms of age distribution. This might have been somewhat different had we been able to recruit secondary schools in all three federal states, but since kindergartens and primary schools agreed to advertise our study much more often than

secondary schools, focusing more on recruiting the latter would probably be necessary to ensure age-related representativeness.

KSW yielded the fewest questionnaires, but due to the small workload, it also had an extremely favorable questionnaire-workload ratio of 41.0, exceeding all others. The strategy was also not representative in age, which might be attributed to the website being more interesting for parents of younger than older children. At the time of our recruitment, the website had just been launched, so while it was advertised in different communities, it was not widely known. During the last months of our recruitment, a subscription function for parents to be informed about studies that fit their children's ages was added. Had this been implemented earlier, it might have increased the participant output for KSW. In general, websites like this are probably an easy and feasible way to recruit participants for online studies if they are widely known and used.

NETWORK was the only recruitment strategy that was neither representative in age nor gender. While the likely demographics of the researchers' networks and the recruitment in a secondary school are compelling explanations for the age-related non-representativeness, the reasons for gender not being representative are rather unclear. Generally, the sample acquired from recruiting in the researchers' networks is likely neither very diverse nor representative of the general population (probably even more so in aspects like educational status than gender and age). While online recruitment does also face challenges in terms of representativeness (Andrade, 2020), it theoretically provides the opportunity to reach more diverse and representative samples compared to traditional experimental studies (Gosling et al., 2004; Gosling et al., 2010; Upadhyay & Lipkovich, 2020). This benefit of online research diminishes when recruiting from own networks, closely resembling the traditional recruitment for in-lab studies. Yet, the advantages of NETWORK recruitment persist, in that it is effective, yielding the highest response rates (both participation and child data rate) compared to all other strategies for which estimating response rates was possible. Additionally, NETWORK features a very favorable questionnaire-workload ratio of 35.7.

TARGET only achieved the second-lowest number of questionnaires, but with a reasonably small workload, and it also was the only recruitment strategy representative of the German population in both age and gender. Overall, TARGET proved to be a worthwhile strategy. Apart from its representativeness, with a questionnaire-workload ratio of 11.9, it was also efficient in terms of workload. Being the most expensive strategy by far – as most of the other strategies hardly cost anything –, however, its drawback lies in the costs.

Lastly, WILD proved moderately effective in recruiting participants, when considering both the number of included questionnaires and the workload: In terms of included questionnaires, it was moderately effective compared to the other strategies, while its questionnaire-workload ratio of 3.4 was the second worst – several times worse than the better ones, but still indicative of more than twice as many included questionnaires per working hour than CLUSTER. Like most strategies, it was not representative regarding age, likely due to the demographics of parents who are active online.

2.2.4.6. Further Remarks on Participant Recruitment

While we recruited participants via various ways, there are of course further possible online recruitment strategies we did not employ. One example is online crowdworking, as described in chapter 2.2.1, which has been used and assessed for online research in the past (e.g., Antoun et al., 2016; Dworkin et al., 2016; Maaravi & Heller, 2020; Semmelmann & Weigelt, 2017). Compared to other ways of recruiting for online studies, it allows more control regarding its recipients, since it is possible to present the advertisement only to workers with specific characteristics. There may also be advantages with regard to diversity. For example, Dworkin et al. (2016) found that when recruiting parents online, the sample from the crowdworking website MTurk was the most diverse compared to e-mail Listservs and Facebook advertisements. However, crowdworkers' attention and motivation may differ from that of other participants due to the guaranteed compensation (except for when it is denied due to missing or incorrect task completion; Dworkin et al., 2016). Including attention check questions into questionnaires distributed via crowdworking websites may thus be helpful. Yet, Dworkin et al. (2016) also report that while this may seem useful, it is not always apparent what to do with the respective data, since their analyses suggested demographic differences between those who correctly answered all attention check questions and those who did not. Due to the guaranteed compensation, crowdworking entails guaranteed costs per participant, and is thus not as cost-effective as most strategies employed by us (when only considering monetary costs excluding the financing of working hours). Lastly, with regard to online crowdworking, there are certain ethical considerations that should be taken into account (Stewart et al., 2017; Woods et al., 2015), and since there are various crowdworking websites available, researchers should make an informed decision regarding which one(s) to use.

A further strategy we did not explore is to place payed advertisements, e.g. or in search engine results or on social media for users fitting the targeted demographics. This strategy has also been reported on in the past (Antoun et al., 2016; Arcia, 2014; Dworkin et al., 2016; Pedersen et al., 2015). However, with regard to Facebook advertisements, Dworkin et al. (2016) elaborate that they seem most successful when researchers target individuals

with an easily identifiable, specific characteristic (e.g., vegans), but they were not successful in recruiting a general sample of parents (Dworkin et al., 2016). Again, this strategy comes with guaranteed recruitment costs – this time not even per successful participation, but for placing the advertisements –, and the average cost per recruited participant has been reported several times higher than that of our TARGET strategy (Antoun et al., 2016; Arcia, 2014).

Finally, conducting the study amidst the Covid-19 pandemic presumably influenced recruitment to a certain degree. On the one hand, people likely spent more time online during lockdowns or quarantine, or due to generally staying at home more. For example, internet traffic increased substantially at the time of initial responses and lockdowns due to Covid-19 in Europe in March 2020 (Feldmann et al., 2020). Furthermore, German participants indicated increased digital media usage in surveys conducted between March and May 2020 (GWI, 2020; Havas Media, 2020), and in a survey in May 2020, a large percentage of participants also indicated that they expect to continue their increased social media usage (PwC, 2020). People might also have been somewhat inclined to support online research during the Covid-19 pandemic as a means to support each other. On the other hand, a representative survey in Germany showed a significant increase in parental stress during the pandemic (Calvano et al., 2022), so parents may have been too preoccupied to participate. The pandemic probably also had implications regarding the selection and success of distribution means in institutions that advertised our study. For example, without it, more institutions might have advertised the study via posters on their premises or hand-outs – and in the institutions who chose those means nonetheless, the participation rate might have been higher if potential participants would have been allowed to spent more time on the premises, which was often restricted due to Covid-19. Yet, the pandemic-related increased electronic communication might also have been beneficial for recruitment in institutions that distributed our study advertisement electronically, as this might not have been possible as easily prior the pandemic. These Covid-19 related aspects should therefore be considered when, for example, incorporating findings from our report into own recruitment planning.

2.2.4.7. Conclusion

Once again, it should be mentioned that the present work is a report on our experiences in participant recruitment for Study 3, and so data collection was not specifically designed for the analyses presented here. Thus, some of the data is of a rather anecdotal nature, some consists of estimates, and not all potentially relevant information is available for all strategies. To examine certain aspects of this report more thoroughly, one would have to specifically collect the missing information. For example, in order to better assess aspects of demographic diversity and representativeness, it may be worthwhile to cover more

aspects – like SES, educational status or geographical location – in data collection. Further aspects on the researcher side could be investigated (in more detail) as well, for example duration or amount of work required to achieve a pre-set sample target size.

With this in mind, we can generally conclude that each assessed recruitment strategy has specific advantages and disadvantages, and which strategies are most useful in a particular situation very much depends on factors like the aim of the data collection and available resources. We hope that we were able to provide a comprehensive insight into execution and results as well as our experiences with various recruitment strategies for online research that may assist others choosing their course of action.

2.2.5. Acknowledgements

Thank you to Carina Schücker for helping to create the questionnaires as well as to Marie Hönemann, Sophia Strobel, Lisa-Marie Tommes and Antonia Zabel for piloting the questionnaires and for all your work in the recruitment of participants.

2.3. Study 3:

Spectacle Ownership and Myopia in German Youth – Findings From Online Questionnaires and Their Relation to Refractive Data

Abstract: Monitoring the prevalence development of myopia is crucial for prevention, diagnostics and intervention efforts. While refractive measurements are commonly employed to estimate myopia prevalence, they are resource-intensive and challenging for large, representative samples. Questionnaire data may be helpful to investigate aspects of myopia prevalence, and online questionnaire theoretically offer a good opportunity to obtain a broad and large sample. In this study, we distributed a short, online parent questionnaire regarding the spectacle ownership of under-18-year-olds in Germany. In total, we collected 1,082 analyzable questionnaires with data from 1,747 children. Additionally, parents were given the option to also complete a longer questionnaire, yielding 221 analyzable questionnaires with data from 341 children. Data from the short questionnaire revealed a 22.2% prevalence of spectacle ownership. Furthermore, 11.6% of the total sample owned spectacles due to myopia, thus making myopia the most common reason for spectacle ownership. Other questionnaire studies from Germany show similar prevalence rates, and our study also replicated typical age- and gender-related patterns regarding myopia prevalence. This indicates that our questionnaire was generally usable to collect such data. However, a comparison with refractive data suggests that questionnaire data overestimate myopia prevalence (more specifically, the prevalence of individuals owning a visual aid due to myopia). Thus, questionnaires are likely not ideal for estimating absolute prevalence rates, but rather for monitoring prevalence and investigating relationships within the measured data. With the long questionnaire, we were able to obtain interesting and relevant aspects regarding eye health care, indicating that underage spectacle owners seem to receive adequate care, while there is more room for improvement for those without spectacles. Overall, questionnaires appear to be a valuable tool for exploring aspects of spectacle ownership and myopia prevalence, though one should be aware of their limitations, particularly regarding absolute prevalence estimations.

2.3.1. Introduction

Monitoring prevalence development over time and in relation to demographic factors is important – especially in case of (suspected) prevalence changes, which may have implications for prevention, diagnostic, and intervention efforts. One such example is myopia prevalence: The global prevalence of myopia is increasing and, barring effective myopia control interventions, is expected to reach 49.8% in 2050 (Holden et al., 2016). In parts of East Asia, there are extremely high myopia prevalence rates of up to 90% in adolescents and young adults (Dolgin, 2015; Morgan et al., 2018). In Europe, the prevalence rates are considerably lower (Xiang & Zou, 2020), though a general increase in myopia prevalence has also been found (Holden et al., 2016).

Not only prevalence rates, but also the amount of available data varies globally. In Europe, there are only few myopia prevalence estimates for children and adolescents based on refractive measurements (for reviews, see: Grzybowski et al., 2020; Xiang & Zou, 2020). Yet, in modern societies, myopia mostly appears during the time when children attend school (Morgan et al., 2021). This school myopia (or juvenile myopia) initially appears in late childhood or adolescence, with varying specifications regarding the exact age – for example, 9-11 years (Gilmartin, 2004) or 8-14 years (Morgan & Rose, 2005). Prevalence data on children and adolescents is therefore especially relevant to monitor myopia development. As for Europe overall, there is also only few data on myopia prevalence rates from refractive measurements for Germany (Study 1; Kaymak et al., 2022; Truckenbrod et al., 2021).

Obtaining refractive measurements from large samples is laborious and expensive. Thus, questionnaire data may be helpful for (some) estimations regarding myopia prevalence. There are a few investigations on children's and adolescents' myopia prevalence in Germany using questionnaire data (e.g., Jobke et al., 2008; Schuster et al., 2020), the respective surveys having been conducted at the latest in 2008 (Jobke et al., 2008) as well as 2003-2006 and 2014-2017 (Schuster et al., 2020), respectively. Jobke et al. (2008) report myopia prevalence rates of 0% in 2-6-year-olds, of 5.5% in 7-11-year-olds, and of 21.0% in 12-17-year-olds. In their 2014-2017 survey, Schuster et al. (2020) found a 11.4% myopia prevalence (0-17-year-olds), again increasing from close to 0% at 0-1 years to ca. 23% (35%) in males (females) aged 16-17 years (see Figure in Schuster et al., 2020). Due to the global trends in myopia, its associated public and individual economic and financial burden (Holden et al., 2014; Naidoo et al., 2019) and potentially severe secondary pathologies (Holden et al., 2014; Saw et al., 2005), more and recent prevalence data would be desirable to monitor the development of myopia prevalence and investigate associated factors.

The latter is especially relevant as myopia prevalence varies dependent on demographic factors, knowledge about which may contributed to targeted prevention, intervention, diagnostics measures. For example, myopia prevalence has repeatedly been shown to increase with age throughout childhood and adolescence, and especially from late childhood onwards (Rudnicka et al., 2016) – in line with school myopia. Furthermore, while prevalence rates are similar in young girls and boys, a higher prevalence in girls seems to emerge in middle childhood, and the difference then further increases throughout adolescence. Rudnicka et al. (2016) state that sex differences of myopia prevalence appear around the age of 9 in white and East Asian populations, and increase throughout adolescence. At the age of 18, white females are twice as likely as white males to be myopic (Rudnicka et al., 2016).

Lastly, it is important to regularly assess children's and adolescents' eyes and vision. Not only do uncorrected refractive errors constitute the major cause of visual impairment globally (Pascolini & Mariotti, 2012), but especially during school age, regular eye examinations could prevent newly developed myopia from going undetected. Amongst other problems, uncorrected myopia can impair school performance: In a study with fourth and fifth graders in China, providing free spectacles to myopic children significantly improved their mathematics' performance (X. Ma et al., 2014). In cases of known refractive errors (and existing correction), its progression should be monitored, and the fit of the refractive correction tested regularly, as undercorrection of myopia seems to cause faster progression than full correction (for a review, see: Logan & Wolffsohn, 2020). For example, the American Optometric Association (AOA) recommends comprehensive eye exams at 6-12 months of age, at least once between 3 and 5 years of age, prior first grade, and then annually through the ages of 6-17 years for asymptomatic or low risk individuals (American Optometric Association, n.d.).

From a methodological standpoint, it is relevant to consider whether and to what extent (online) questionnaire studies can generate reliable prevalence data. Questionnaires, especially if they can be filled in online, offer great opportunities for broad distribution and data collection from large samples at relatively low cost. On the other hand, issues such as participation bias (sample not representative of the underlying population, leading to non-generalizable results), survey fraud (taking an online survey multiple times) or response biases (giving incorrect answers for various reasons, e.g. due to inattentiveness) pose potential problems (Andrade, 2020; Elston, 2021; Singh & Sagar, 2021; Wetzel et al., 2016). In terms of refraction data, Landmann and Bechrakis (2013) conducted a questionnaire study on ametropia and family history in children and adolescences. They concluded that questionnaires pose an adequate opportunity conduct at least a rough review of a population's refraction problems to gain important, additional insights in this regard (Landmann & Bechrakis, 2013). In general, while there is certainly potential in respective

questionnaire data, it is important to critically consider which conclusions may or may not be derived from such data. With regard to myopia – or ametropia in general – prevalence rates, it may also be helpful to compare the questionnaire data to data from refractive measurements.

To obtain prevalence data on spectacle ownership in general, and especially due to myopia, as well as associations with some demographic factors in children and adolescents in Germany, we distributed online parent questionnaires regarding children's spectacle (or contact lenses) ownership. As will be explained in detail later (see chapter 2.3.2), we believe that the prevalence of spectacle ownership due to myopia can be roughly equated with the prevalence of known myopia. We also assessed questionnaire data with respect to check-ups regarding spectacle need and spectacle fit. Furthermore, we wanted to critically assess the usefulness of questionnaires to gain a representative sample via various recruitment strategies and to estimate such prevalence data. The samples acquired via the different recruitment strategies and associated insights on their representativeness have been discussed in-depth in Study 2. Here, we focus on the obtained prevalence data, associations with demographic factors, as well as check-ups regarding spectacle need or fit, and we discuss considerations on the validity of data acquired from different questionnaires and compared to refractive data.

2.3.2. Methods

2.3.2.1. Study Design

All questionnaires were created in LimeSurvey and could be filled in by parents (or caregivers) for up to five children. Parents of children below the age of 18 and living in Germany were recruited to fill in a short, anonymous questionnaire on their children's spectacle ownership. Throughout the questionnaire, all questions regarding spectacles were phrased to include contact lenses as well. Accordingly, the ownership of contact lenses is also included when spectacle ownership is referred to in the following. In the **short questionnaire**, parents indicated their children's month and year of birth, whether their children owned spectacles and if so, if this was due to hyperopia, myopia, an unknown reason, and/or any other reason. The latter required written specification. Upon completion of the short questionnaire, participants could participate in an additional questionnaire on the same topic, referred to as **long questionnaire**. If the children for which the long questionnaire was filled in owned spectacles (again, or contact lenses), it enquired about the spectacles' specifications and the last time they were assessed by an eye health professional. If said children did not have spectacles, parents answered questions about their children's potential sight problems, past eye health check-ups, school entry age, near work time and outdoor

time. In either case, the long questionnaire concluded with questions about the biological parents' ocular health.

We wanted to keep the short questionnaire as simple as possible to reduce drop-out and incorrect answers. Therefore, we did not directly ask about potential diagnoses (e.g., myopia) as we feared this might confuse potential participants, or they might not know – as for example Schuster et al. (2020) report that 13.7% of parents in their sample did not know whether or not their child was myopic. Instead, we enquired about spectacle ownership (and the reasons), as we assumed that whether their children owned spectacles would be easy for participants to answer, and the possibility to indicate the reason as unknown would encourage participants to continue the questionnaire even if that was the case. If myopia is diagnosed in a child or adolescent in Germany, it is reasonable to assume that it is also corrected. For one, a full correction is generally recommended for myopia (Logan & Wolffsohn, 2020) and for Germany, a myopia correction is recommended for the age-appropriate visual attention space (Berufsverband der Augenärzte Deutschlands e.V. & Deutsche Ophthalmologische Gesellschaft e.V., 2010). Thus, it may be possible that a baby or toddler with diagnosed low myopia would not be corrected (because their visual attention space does not extend far into the distance) – but apart from that, correction of myopia is recommended. Furthermore, at least the spectacle lenses are usually covered by health insurance for children and adolescents. We therefore believe that corrected myopia is a reasonable estimator for diagnosed myopia – although of course there may still be cases in which a family knows about a child's refractive error, but does not take any measures to correct it. It is important to note that this data only provides prevalence estimations on refractive errors that are diagnosed and corrected – and other than myopia, a correction is not always recommended for hyperopia (Berufsverband der Augenärzte Deutschlands e.V. & Deutsche Ophthalmologische Gesellschaft e.V., 2010). Thus, while we report prevalence rates for spectacle ownership in general as well as all individual reasons, as per the main objective of this investigation, we mostly focus on the prevalence of spectacle ownership due to myopia.

2.3.2.2. Recruitment

Five recruitment strategies were used to distribute the short questionnaire between September 2020 and January 2022. In this work, these strategies are discussed only in case we suspected a potential influence on the analyzed data. Their in-depth description and discussion can be found in Study 2. Briefly, the strategies were as follows:

CLUSTER describes the participant recruitment in German schools and kindergartens selected via *multistage cluster sampling.* Five counties were randomly selected out of three randomly selected federal states[4]. Then, we created randomized lists of kindergartens, primary and secondary schools for each of the 15 counties, excluding institutions for children with special needs only, but including those for children with and without special needs. We then contacted a number of institutions from each list and asked them to distribute our questionnaire. Since we were not able to get the respective ministry for one federal state to assess our study, kindergartens were recruited in all three, but schools only in two federal states.

In KSW, we recruited participants via "Kinder schaffen Wissen" (kinderschaffwissen.eva.mpg.de, "children create knowledge"), a website to advertise online studies from German-speaking countries to potential parent and child participants.

NETWORK describes the questionnaire's distribution in the researchers' personal and professional networks, like posting it on private social media, asking acquaintances to participate, or distributing it in educational institutions the researchers were connected to.

In TARGET, we requested the names and addresses from everyone under the age of 18 living in six randomly chosen postal codes in the city of Dortmund from the population register. We then randomly chose 100 families from each of these postal codes and sent them a letter inviting them to participate. We did this twice, thus sending a total of 1,200 letters.

Lastly, in WILD, the questionnaire was distributed in online forums, Facebook groups, and via Instagram influencers. Apart from a few examples like Facebook groups for survey participants, we only posted in forums and groups where we expected most members to be parents, and we approached Instagram influencers addressing topics like parenthood or children.

It should be mentioned that an overlap between different recruitment strategies with regard to recipients or participants of the questionnaire is very unlikely. Of course, overlaps are theoretically possible, for example, if parents both received the questionnaire via the child's educational institution (CLUSTER) as well as found it in an online forum (WILD). The locations of the different recruitment strategies were, however, chosen with the need to avoid overlaps in mind, and we for example did not distribute the questionnaire via NETWORK in the vicinity of the TARGET recruitment areas. Therefore, although an overlap in recipients or participants of the individual strategies can of course not be ruled out with absolute certainty, it should only have occurred – if at all – in very isolated cases. We thus consider the data from the different recruitment strategies to be independent.

[4] The random selection of federal states occurred within some pre-set restraints that are explained in Study 2.

2.3.2.3. Participants

In total, we received 1,098 completed short questionnaires. Of those, we excluded 16 questionnaires for reasons described in chapter 2.3.2.4 – leaving 1,082 questionnaires with data from 1,747 children for analysis. We also received 225 completed long questionnaires. Exclusion of four questionnaires left 221 long questionnaires with data from 341 children for analysis. Demographic information of the analyzed samples is presented in Table 2.12. As can be seen, the number of children for which data was collected differs between recruitment strategies. To reiterate, the recruitment strategies are discussed here only in so far as a potential influence on the analyzed data was suspected. Beyond that, they are elaborated upon in Study 2.

Table 2.12

Demographic Information for Analyzed Samples

	short questionnaire	**long questionnaire**
questionnaires (*N*)	1,082	221
children (*N*)	1,747	341
- per questionnaire (*M±SD)*	1.61±0.71	1.54±0.68
- per gender (*N*)		
female	858	163
male	888	178
non-binary	1	0
- per age group (*N*)		
0-2 years	217	55
3-5 years	305	74
6-8 years	320	73
9-11 years	301	56
12-14 years	355	56
15-17 years	249	27
- per recruitment strategy (*N*)		
CLUSTER	340	26
KSW	140	56
NETWORK	821	144
TARGET	215	66
WILD	231	49

2.3.2.4. Data Analysis

Prior data analysis, we excluded questionnaires with implausible data (e.g., "5" given as year of birth) or did not fit the inclusion criteria (e.g., "child" reported on over 18 years). As described above, we excluded 16 short and four long questionnaires.

We then analyzed prevalence data based on the short questionnaire. This was because (1) data from the short questionnaire was sufficient to generate prevalence rates, (2) we had only few data from the long questionnaire, and (3) we suspected a participation bias regarding the long questionnaire: As parents from spectacle-owning children needed to check the eyeglass prescription for the spectacles' values, filling in the questionnaire was probably more laborious for them than for parents of spectacle-free children. Thus, we suspected that parents from spectacle-owning children would more likely be discouraged from completing the long questionnaire than parents from spectacle-free children.

Therefore, we focused on the short questionnaire for analyzing the prevalence of children owning spectacles overall, as well as due to myopia, hyperopia, other reasons, and unknown reasons. We also analyzed said prevalence rates per age group (with age being divided into six groups encompassing 3 years each) and gender (with only females and males analyzed individually as there is only one non-binary participant in the sample). We conducted these analyses for the complete sample and for spectacle owners only. Furthermore, we assessed the prevalence rates for spectacle ownership due to myopia in the complete sample per gender and age group together.

We then compared the prevalence of spectacle ownership between short and long questionnaire. From the long questionnaire, we also assessed two aspects regarding eye health care: For spectacle-owning children, we analyzed when their values had last been assessed by an eye health professional. For spectacle-free children, we analyzed if they ever reported or showed any vision difficulties as well as if and how long ago the potential need for spectacles had ever been assessed.

2.3.3. Results

2.3.3.1. Prevalence of Spectacles Overall and per Gender

Overall, 22.2% of children in the sample owned spectacles. With regard to the reasons, 11.6% had spectacles due to myopia, 8.2% due to hyperopia, 4.1% due to other reasons (e.g., astigmatism), and 0.9% due to unknown reasons. Table 2.13 shows the prevalence rates of owning spectacles overall and for specific reasons for all genders as well as girls and boys individually. As can be seen, the prevalence of spectacles is 7.9% higher for females than males, and a higher percentage of females than males own spectacles due to

myopia. The prevalence rates for spectacle ownership for reasons other than myopia are relatively similar between genders, though the prevalence of other reasons for spectacles is slightly higher in females than males.

Accordingly, myopia is also the most prevalent reason for spectacles in the data of spectacle owners only, and the respective gender difference regarding myopia is also present. Other than for the overall sample, the prevalence rates of hyperopia as a reason for spectacles as well as the reason being unknown are somewhat higher in males than in females for spectacle owners only. The prevalence of other reasons for spectacle ownership are mostly comparable between genders, though again slightly higher for females than males. Thus, overall, myopia is the main reason for spectacles, and the prevalence of myopia as reason for spectacles is higher in females than males.

Table 2.13

Prevalence of Spectacles for the Complete Sample and per Gender

	all children	**females**	**Males**
% (standard error) based on complete (sub)sample			
owning spectacles	**22.2 (1.0)**	**26.1 (1.5)**	**18.2 (1.3)**
- reason: myopia	11.6 (0.8)	14.7 (1.2)	8.4 (0.9)
- reason: hyperopia	8.2 (0.7)	8.6 (1.0)	7.9 (0.9)
- reason: other	4.1 (0.5)	5.2 (0.8)	3.0 (0.6)
- reason: unknown	0.9 (0.2)	0.7 (0.3)	1.1 (0.4)
% (standard error) based on spectacle owners within (sub)sample			
- reason: myopia	52.2 (2.5)	56.3 (3.3)	46.3 (3.9)
- reason: hyperopia	37.2 (2.5)	33.0 (3.1)	43.2 (3.9)
- reason: other	18.6 (2.0)	20.1 (2.7)	16.7 (2.9)
- reason: unknown	4.1 (1.0)	2.7 (1.1)	6.2 (1.9)

Note. As the questionnaire allowed specification of several reasons for owning spectacles, the sum of the reason-specific prevalence rates may exceed 100%. For all participants with the reason for spectacles given as unknown, no other reason was given. The data of all genders is based on one more participant than the data of males and females combined due to one non-binary participant.

While the different recruitment strategies may impact the estimated prevalence rates, the prevalence of owning spectacles overall and per gender is mostly comparable between strategies, despite some variation. For three out of five strategies, the overall prevalence ranges between 19.7% and 23.5%, thereby being close to the total sample's prevalence (see Table 2.13). Likewise, the prevalence rates for spectacle ownership range from 26.1% to 30.0% for females and from 14.0% to 18.5% for males in four recruitment strategies each. Two strategies fall somewhat out of this pattern: While the prevalence for females lies within the above range for KSW, a 32.0% prevalence was obtained for males, and a 29.3% prevalence overall. Conversely, the prevalence for males lies within the above range for TARGET, but the prevalence for females is 12.9%, and the overall prevalence 14.9%. As can be seen in Study 2 (Table 2.10), the age distribution does not explain the diverging overall prevalence rates for these strategies – i.e., there were not predominantly older (younger) children in KSW (TARGET), which might have explained these differences as spectacle ownership is generally more prevalent in older than younger children and adolescents (see below). Likewise, the gender distribution of the KSW and TARGET participants is relatively similar to that of the total sample, and there was also no apparent interaction in the distribution of gender and age group that would explain the observed prevalence differences. Overall though, the prevalence rates are comparable between strategies, and thus we do not generally suspect a strong bias regarding spectacle ownership for both the total sample as well as females and males separately due to the different strategies.

2.3.3.2. Prevalence of Spectacles per Age Group

Table 2.14 presents the prevalence rates of owning spectacles overall and for specific reasons per age group. It is readily apparent that the prevalence of spectacle ownership increases with age, as does the prevalence of myopia as the reason for spectacles. Only 0.5% of the 0-2-year-olds have spectacles due to myopia, while 26.5% of the 15-17-year-olds do. Between the three youngest age groups, there also is an increase in the prevalence of owning spectacles due to hyperopia in the complete sample. While this increase even exceeds that of the corresponding prevalence for myopia at these ages, said prevalence for hyperopia remains constant for the age groups after that, whereas that for myopia continues to increase.

Furthermore, among spectacle owners, the ratio of myopia to the other reasons for having spectacles differs between age groups: While myopia increases continuously with age until reaching 71.0% among 15-17-year-olds, the prevalence rates of the other reasons remain relatively constant or decrease with age. The latter is particularly evident for hyperopia, as 66.7% of the 0-2-year-old spectacle owners own spectacles because of hyperopia, and only 21.5% of the 15-17-year-old spectacle owners do. Thus, there is a consistent increase of

spectacle ownership with age, and from middle childhood onwards, the main reason for that seems to be an increase in myopia prevalence.

Table 2.14

Prevalence of Spectacles per Age Group

	0-2 years	**3-5 years**	**6-8 years**	**9-11 years**	**12-14 years**	**15-17 years**
% (standard error) based on complete (sub)sample						
owning spectacles	**2.8 (1.1)**	**11.1 (1.8)**	**20.0 (2.2)**	**22.6 (2.4)**	**34.4 (2.5)**	**37.3 (3.1)**
- reason: myopia	0.5 (0.5)	2.6 (0.9)	6.3 (1.4)	10.0 (1.7)	21.7 (2.2)	26.5 (2.8)
- reason: hyperopia	1.8 (0.9)	6.9 (1.5)	10.9 (1.7)	9.0 (1.6)	10.4 (1.6)	8.0 (1.7)
- reason: other	0.9 (0.7)	2.3 (0.9)	5.9 (1.3)	5.3 (1.3)	4.5 (1.1)	4.8 (1.4)
- reason: unknown	0.0 (0.0)	1.0 (0.6)	1.3 (0.6)	1.0 (0.6)	0.6 (0.4)	1.6 (0.8)
% (standard error) based on spectacle owners within (sub)sample						
- reason: myopia	16.7 (1.7)	23.5 (7.4)	31.3 (5.8)	44.1 (6.1)	63.1 (4.4)	71.0 (4.7)
- reason: hyperopia	66.7 (2.1)	61.8 (8.5)	54.7 (6.3)	39.7 (6.0)	30.3 (4.2)	21.5 (4.3)
- reason: other	33.3 (2.1)	20.6 (7.0)	29.7 (5.8)	23.5 (5.2)	13.1 (3.1)	12.9 (3.5)
- reason: unknown	0.0 (0.0)	8.8 (5.0)	6.3 (3.0)	4.4 (2.5)	1.6 (1.2)	4.3 (2.1)

Note. As the questionnaire allowed specification of several reasons for owning spectacles, the sum of the reason-specific prevalence rates may exceed 100%.

In the individual recruitment strategies, the pattern of an increasing spectacle prevalence with higher age is also generally present, though not as consistent as for the total sample – i.e., there are some deviations from this pattern within some strategies. Furthermore, there sometimes are larger differences in the prevalence of spectacle ownership between strategies as well as between the total sample and an individual strategy. For example, out of the 30 prevalence rates calculated per age group for the individual strategies (6 age groups x 5 strategies), nine deviate from the total sample's prevalence rate

for said age group by ≥ 10% (see Supplementary Table B1). As the sample sizes per age group are often rather small for the individual strategies, the sometimes large prevalence differences are unsurprising: Of said 30 prevalence rates, 20 – including all of the nine deviating prevalence rates – are based on a sample size of < 50, and seven even on a sample size of < 30.

When assessing the prevalence data per age group, the marked increase in prevalence in spectacle ownership between the age groups 9-11 years and 12-14 years stands out. Concurrently, there is a substantial increase in the prevalence of myopia as a reason for spectacles between these age groups, while prevalence rates for the remaining reasons remain constant. This finding coincides well with the age(s) at which school myopia usually first appears (Gilmartin, 2004; Morgan & Rose, 2005). It should be noted though that there are more males than females in each age group up to and including the ages 9-11 years (see Table 2.10 in Study 2). Thereafter, this pattern is reversed. Since a higher myopia prevalence in adolescent females than males has repeatedly been shown (Rudnicka et al., 2016), this might be one explanation for the marked increase in the prevalence of spectacle ownership between the above-mentioned age groups. Yet, as can be seen in Figure 2.6, the large increase in said prevalence between the age groups of 9-11 and 12-14 years is also apparent in females and males individually, and thus cannot be explained by gender ratio alone.

2.3.3.3. Prevalence of Spectacles Due to Myopia per Age Group and Gender

As per the focus of this investigation, the prevalence of spectacle ownership due to myopia was examined more closely. Figure 2.6 displays said prevalence for the complete sample, split into age groups and genders, clearly showing an overall prevalence increase. Furthermore, the previously discussed steeper increase of spectacle ownership prevalence due to myopia between the age groups 9-11 years and 12-14 years, coinciding with the age of school myopia appearance, is well visible. There also is a generally higher prevalence of spectacle ownership due to myopia in females than males, apart from in the age group 3-5 years, in which said prevalence is very low overall. This gender difference generally increases with age – with the exception of a higher gender difference in the age group 9-11 years than the two older ones.

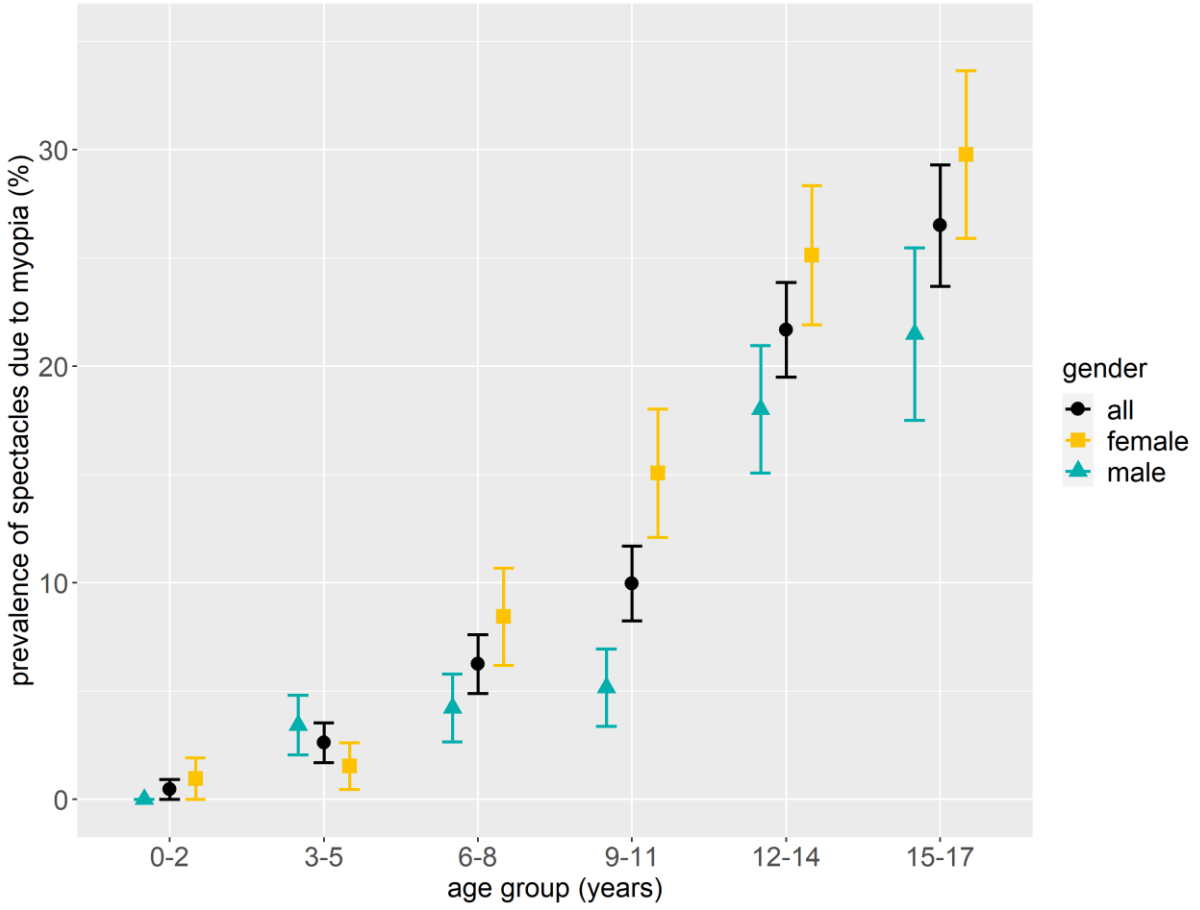

Figure 2.6. Prevalence and standard error of spectacle ownership due to myopia per gender and age group. The data for all genders includes one more participant than the data of males and females combined due to one non-binary participant.

With regard to the different recruitment strategies, the prevalence rates of spectacle wear due to myopia range from 7.4% to 13.5% between them. Both TARGET (7.4%) and CLUSTER (8.8%) exhibit prevalence rates below the overall rate of 11.6%, while KSW (12.1%), WILD (12.1%) and NETWORK (13.5%) exhibit higher rates (see Supplementary Table B2 for prevalence rates of spectacle wear due to myopia per recruitment strategy and age group). Thus, while the prevalence difference between recruitment strategies is not extreme, there is some variation, with the largest difference between TARGET and NETWORK. This topic will be revisited in chapter 2.3.4.

2.3.3.4. Prevalence Rates: Short Versus Long Questionnaire

Unsurprisingly, the prevalence rates for spectacle ownership were lower in the long than the short questionnaire: In the long questionnaire's data, only 10.0% (standard error: 1.6) of the complete sample owned spectacles, as did 11.0% (standard error: 2.5) of females,

and 9.0% (standard error: 2.1) of males. For reference, 22.2% of all children as well as 26.1% of females and 18.2% of males from the short questionnaire owned spectacles (see Table 2.13). As already mentioned in Methods, participants with spectacle-owning children were believed to have an increased participation effort with the long questionnaire in contrast to participants with spectacle-free children. We therefore suspect a participation bias in the long questionnaire in that people with spectacle-owning children disproportionally often did not complete the long questionnaire following the short one. Since all participants of the short questionnaire had the opportunity to participate in the long questionnaire, the substantially lower prevalence of spectacle ownership in the long questionnaire's data compared to that of the short questionnaire supports this assumption. Therefore, and because within the long questionnaire's data, there were only 34 spectacle-owning children overall, we did not analyze the prevalence rates from the long questionnaire further.

2.3.3.5. Children With Spectacles: Last Assessment of Spectacle Fit

One aspect that we did analyze for spectacle-owning children from the long questionnaire was the last time the spectacles' fit was assessed by an eye health professional. As the sample for this analysis is rather small, the respective result needs to be considered with caution – yet, it provides interesting information about general eye health care. Of the 34 children owning spectacles, 26 (76.5%) had their last assessment of the spectacles' specifications within the last half year, six (17.6%) more than half a year but not more than one year ago, and two (5.9%) more than one year but not more than 2 years ago. The latter two children are from the age groups 6-8 years and 15-17 years, respectively. Generally, it is a promising outcome that for the vast majority of spectacle-owning children, the appropriateness of the spectacles' specifications was tested within the last year.

2.3.3.6. Children Without Spectacles: Visual Difficulties and Need for Spectacles

Of the 307 spectacle-free children from the long questionnaire, 31 (10.1%) have reported or shown vision problems in the past. Furthermore, for 238 (77.5%) of the spectacle-free children, the potential need for spectacles had at least been assessed once. Table 2.15 shows the time since the last assessment for the overall group and each age group separately, showing that for the majority of those who ever had the potential need of spectacles assessed, this had been done within the last 2 years. This is especially promising with regard to the older age groups, for whom school myopia onset is an issue.

Table 2.15

Time of Last Assessment Regarding Spectacle Need for Spectacle-Free Children

	years since last assessment number of children (% of all spectacle-free children)							
age group	**any time**	**≤ ½**	**> ½ & ≤ 1**	**> 1 & ≤ 2**	**> 2 & ≤ 3**	**> 3 & ≤ 4**	**> 4 & ≤ 5**	**> 5**
all	**238 (77.5%)**	**67 (21.8%)**	**57 (18.6%)**	**51 (16.6%)**	**34 (11.1%)**	**15 (4.9%)**	**6 (2.0%)**	**8 (2.6%)**
0-2 years	**20 (37.0%)**	12 (22.2%)	5 (9.3%)	1 (1.9%)	2 (3.7%)	0 (0%)	0 (0%)	0 (0%)
3-5 years	**44 (63.8%)**	14 (20.3%)	17 (24.6%)	10 (14.5%)	2 (2.9%)	0 (0%)	1 (1.4%)	0 (0%)
6-8 years	**63 (92.6%)**	16 (23.5%)	18 (26.5%)	15 (22.1%)	10 (14.7%)	2 (2.9%)	1 (1.5%)	1 (1.5%)
9-11 years	**47 (95.9%)**	12 (24.5%)	6 (12.2%)	10 (20.4%)	10 (20.4%)	4 (8.2%)	2 (4.1%)	3 (6.1%)
12-14 years	**43 (95.6%)**	9 (20.0%)	7 (15.6%)	11 (24.4%)	8 (17.8%)	5 (11.1%)	2 (4.4%)	1 (2.2%)
15-17 years	**21 (95.5%)**	4 (18.2%)	4 (18.2%)	4 (18.2%)	2 (9.1%)	4 (18.2%)	0 (0%)	3 (13.6%)

Note. The absolute number shows the number of spectacle-free children who had their last assessment regarding the need of spectacles within the given timeframe. The percentage shown is based on all spectacle-free children of the respective age group.

For 30 of the 31 children who had reported or shown vision problems before, a past assessment regarding the need of spectacles was also reported. This is generally encouraging, though of course we do not know whether this assessment had taken place before or after said vision problems.

2.3.4. Discussion

2.3.4.1. Summary of the Results

We distributed a short parent questionnaire on spectacle ownership in children and adolescents via multiple recruitment strategies. The short questionnaire was followed by the option to fill in a long(er) questionnaire inquiring – amongst others – about the spectacles' values in case of spectacle-owning children. The short questionnaire's data show a total

prevalence of 22.2% for spectacle ownership among under 18-year-olds in Germany. Myopia was the most prevalent reason for owning spectacles – with 11.6% of the total sample and 52.2% of spectacle-owners having spectacles because of myopia. Furthermore, we replicated the age-typical development of myopia: In younger ages – up until the age group of 6-8 years –, hyperopia was a more prevalent reason of spectacle ownership than myopia, and myopia became more prevalent from the age group of 9-11 years onwards. Both the prevalence of spectacle ownership as well as myopia as a reason increased with increasing age, with an especially large incline between the age groups of 9-11 and 12-14 years. Our data also shows typical gender differences of myopia prevalence, with a higher prevalence in girls than boys especially from the age group 9-11 years and onwards – although different than usually reported for myopia prevalence in comparable populations (Rudnicka et al., 2016), the largest gender difference in spectacle ownership due to myopia was in our 9-11 years age group instead of the older ones. For readability and term-wise consistency with other questionnaire studies, "myopia prevalence" refers to the prevalence of owning spectacles due to myopia when discussing this study's data in the following parts of the discussion.

As expected, spectacle ownership prevalence rates were lower in the long than the short questionnaire, presumably due to a participation bias, as it was more work for parents of spectacle-owning children than spectacle-free children to fill in the long questionnaire. We therefore did not analyze spectacle ownership from the long questionnaire any further, but we did assess aspects regarding eye health care. More precisely, all 34 spectacle-owning children for which the long questionnaire was filled in had their spectacles' values last assessed at maximum 2 years ago, 32 of them even at maximum one year ago. Of the 307 spectacle-free children, 77.5% had a past assessment regarding the potential need for spectacles, and 57% had said last assessment at maximum 2 years ago. Furthermore, 31 of the spectacle-free children had vision problems in the past, 30 of which also had a past assessment regarding the potential need for spectacles.

2.3.4.2. Myopia Prevalence From This Versus Other German Questionnaire Studies

Considering other studies from Germany, our data provides insights into the utility of such questionnaires for estimating myopia prevalence rates. Table 2.16 shows the present study's myopia prevalence rates alongside those of two other German questionnaire studies (Jobke et al., 2008; Schuster et al., 2020) as well as those from an investigation we conducted using refractive measurements (Study 1). The results of the present study compared to other German questionnaire studies will be expanded upon now, while the results of the questionnaire studies versus those of refractive measurements will be discussed in the following section.

Table 2.16

Myopia Prevalence from German Questionnaire Studies and Our Refractive Measurements

	German questionnaire studies			refractive measurements (Study 1)	
age (years)	**present study**	**Jobke et al. (2008)**	**Schuster et al. (2020)**	**all myopic participants**	**myopic participants with visual aid**
0-17	11.6		11.4		
0	0.5		0.5 (males) 0.0 (females)		
1					
2	2.6	0.0	2.0 (males) 0.8 (females)		
3					
4			2.5 (males) 3.0 (females)		
5					
6	6.3		5.0 (males) 3.5 (females)		
7					
8		5.5	7.5 (males) 9.0 (females)	8.4	4.1
9	10.0				
10			10.2 (males) 16.0 (females)		
11					
12	21.7	21.0	14.9 (males) 20.2 (females)	19.5	11.1
13					
14	26.5		17.0 (males) 28.2 (females)		
15					
16			23.7 (males) 35.2 (females)		
17					

Note. Gray fields indicate that we have no data from the respective study for the corresponding age groups. The prevalence rates reported for Schuster et al. (2020) are those from the 2014-2017 survey. Also, prevalence rates per age group are only given for males and females individually in Schuster et al. (2020), which is why they are also presented per gender here. For the sake of clarity, the overall numbers are presented for all other studies. Furthermore, the numbers presented here for Schuster et al. (2020) are estimated from the publication's Figure. For Study 1, the age group bounds represent the approximate standard deviations of the respective sample, with the younger (older) sample aged M±SD = 9.30±0.78 years (M±SD = 14.99±1.12 years).

As can be seen in Table 2.16, our myopia prevalence rates are generally comparable to, but somewhat higher than those in Jobke et al.'s (2008) questionnaire study. Other than in our short questionnaire, Jobke et al. (2008) asked participants for information on the spectacles' refraction and confirmed this with the respective opticians. As explained above, we had expected a participation bias for such questions, and likely experienced one with our long questionnaire. Not only the myopia, but also the hyperopia prevalence rates in Jobke et al. (2008) are lower than ours, and their prevalence of emmetropia is considerably higher, so the between-study difference in myopia prevalence cannot simply be explained by e.g. myopia prevalence having increased over time. Keeping the suspected participation bias in mind, it may be possible that parents of spectacle-owning children were differently motivated to participate in Jobke et al.'s (2008) and our questionnaire (for considerations regarding the motivation of parents with spectacle-owning children to take part in our questionnaire, see below) – which might play a part in explaining the slightly different myopia prevalence estimates. This is, however, rather speculative at this point.

Interestingly, our myopia prevalence is very similar to that reported by Schuster et al. (2020) from the data of the German Health Interview and Examination Survey for Children and Adolescents (KiGGS), also with similar trends regarding age and gender. Schuster et al. (2020) considered children and adolescents myopic who were reported to be myopic by their parents, and who were also reported to have a visual aid. The strong similarity in the results possibly suggests that our distribution methods worked well for the acquisition of such data, despite the fact that it entailed less control and knowledge over potential participants than was given in the KiGGS study, which also had a much larger sample than we did (N = 15,023 children included in Schuster et al., 2020). Of course, the data from the KiGGS study is some years older than ours, but based on the baseline study (2003-2006) and wave 2 (2014-2017) of KiGGS, Schuster et al. (2020) concluded that myopia prevalence in children and adolescents in Germany currently does not seem to rise. Assuming that this trend continued beyond this timeframe, their and our data should be generally comparable – although, importantly, this assumption is of course not necessarily true.

2.3.4.3. Myopia Prevalence From Questionnaires Versus Refractive Measurements

With regard to non-questionnaire studies, comparing the present data to Study 1, in which we conducted refractive measurements during the present study's data acquisition period, is noteworthy. As can be seen in Table 2.16, the prevalence of myopia in this study appears to align well with the data from our refractive measurements on first sight, with the prevalence rates for all myopic participants in Study 1 being comparable to that of the corresponding age groups in the present study. However, in Study 1, we also observed that 51.2% (43.3%) of myopic participants in the younger (older) sample did not have a visual aid,

and so they would not have been categorized as myopic – i.e., having spectacles due to myopia – in the present study. Thus, for the data from both studies to be consistent, the prevalence rates from the present study would actually have to match the prevalence of myopic participants who own a visual aid from Study 1 – which is much lower than the myopia prevalence from the present study (see Table 2.16). This discrepancy could indicate a participation bias in the present study, for example, in that parents of spectacle-owning children are more likely to participate than others due to interest in the topic. Another possibility is that the present sample may include more people with higher socioeconomic and/or educational status than the general public. Myopia prevalence is positively associated with both educational and socioeconomic status (Foster & Jiang, 2014; K. M. Williams, Bertelsen, et al., 2015) and myopic parents may also be more likely to have their children's vision tested. An overrepresentation of participants with higher education could apply especially to NETWORK, as a substantial part of the researchers' networks belongs to university-related communities. A comparable scenario might apply to KSW, where participants were recruited via a website, which was predominantly advertised within university-affiliated communities. The myopia prevalence in NETWORK (13.5%) is in fact the highest of all recruitment strategies, followed by KSW and WILD (both 12.1%). These numbers could suggest a participation bias as described, though WILD exhibiting the same prevalence as KSW cannot be explained similarly, as it was advertised on various online platforms. CLUSTER (8.8%) and TARGET (7.4%) exhibit somewhat lower myopia prevalence rates, which indeed fit those in Study 1 better than the other strategies' prevalence rates (see Supplementary Table B2). Yet, they are still considerably higher than the prevalence of myopic participants with visual aids in Study 1 (except for TARGET in the 9-11 years age group; see Supplementary Table B2), so there may have been a bias in these data as well. Overall, these findings indicate a potential education-related participation bias in the present data. Whether such a bias might explain (some of the discrepancies) remains speculative at this point, especially since these considerations are partly based on small sample sizes and involve several assumptions.

It is also theoretically possible that the data from the present study is more reliable than that from Study 1. However, a strong underestimation of myopia prevalence in the latter is improbable due to the non-cycloplegic refractive measurements, which generally lead to overestimation of myopia (Grzybowski et al., 2020; Rudnicka et al., 2016) – though respective measurements with Plusoptix devices have generally been found to have a good measurement accuracy, especially if the individuals are non-hyperopic (Fogel-Levin et al., 2016; Ghadimi et al., 2024; Payerols et al., 2016; Teberik et al., 2018; Wilson et al., 2022). A significant overestimation of the prevalence of uncorrected myopia in Study 1 is also unlikely, as participants should be able to reliably indicate whether they possess a visual aid. Furthermore, in Study 1, the participating schools were selected as randomly and

representatively as possible. Participation did not require a parent's signature, making a significant participation bias with regard to e.g. familial socioeconomic or educational status highly unlikely (Study 1. Moreover, both the reported myopia prevalence rates as well as the high prevalence of uncorrected myopia in Study 1 are consistent with prior literature, as another German investigation measuring refractive data yielded comparable prevalence rates (Truckenbrod et al., 2021) and high rates of uncorrected and/or undiagnosed myopia and refractive errors overall have been demonstrated before (Choy et al., 2020; Popović-Beganović et al., 2018; Jianyong Wang et al., 2020; M. Yang et al., 2018). Therefore, while we cannot exclude that aspects in Study 1 may (also) explain between-study discrepancies in myopia prevalence, an overestimation of myopia prevalence in the present study appears more likely.

Since very similar myopia prevalence rates were obtained here and in the KiGGS study (Schuster et al., 2020; see Table 2.16), one also needs to consider the mismatch between data from the latter and our refractive data (Study 1). Participants in the KiGGS study participated in an extensive survey covering various health-related aspects (Schuster et al., 2020). Therefore, a participation bias based on parents' interest of children's spectacle wear seems implausible. People with lower educational status were underrepresented in the KiGGS study (wave 2, 2014-2017; Hoffmann et al., 2018), which might be one possible explanation for the higher myopia prevalence rates as compared to our refractive data (Study 1) due to the association of myopia and educational status (Foster & Jiang, 2014). Yet, in the KiGGS study, participants were weighted to make the sample representative of the German population with regard to multiple characteristics, including parental educational status (Hoffmann et al., 2018; Schuster et al., 2020). Hoffmann et al. (2018) state that by this, the impact of demographic deviations from the general population on the obtained health parameters could partly be corrected. Thus, such sociodemographic factors might have impacted the results of Schuster et al. (2020), but we cannot determine if and to what extent this was the case. Another explanation for the differing prevalence rates might be that participants of comprehensive health studies are more health-conscious than the general public. They may be more inclined to seek medical attention, including vision testing, which could result in a lower rate of uncorrected or undiagnosed myopia. However, these speculations cannot be empirically verified at this point.

Interestingly, the data from the present study's long questionnaire fits the myopia prevalence of our refractive data (Study 1) better than that of the short questionnaire. Due to aforementioned considerations – e.g., more parents of spectacle-owning than spectacle-free children having discontinued participation after the short questionnaire –, we did not analyze prevalence rates from the long questionnaire. However, for the purpose of this discussion, we computed the myopia prevalence for the age groups roughly corresponding the Study 1 data, revealing the following prevalence rates of spectacles correcting myopia in the long

questionnaire's data: 1.4% in 6-8-year-olds, 7.1% in 9-11-year-olds, 7.1% in 12-14-year-olds, and 11.1% in 15-17-year-olds, fitting the prevalence rates of myopic participants owning visual aids in Study 1 considerably better than the data from the short questionnaire (see Table 2.16). One might speculate that the different participation biases suspected for the short and seen for the long questionnaire have, in a sense, counterbalanced each other, leading to more accurate prevalence estimates as compared to refractive data – however, this is highly speculative and based on multiple presumptions, and the matching data could also simply be coincidental.

Overall, generating robust prevalence estimates – for example for (corrected) myopia – from questionnaire data seems to be quite challenging, and our results underscore Landmann and Bechrakis' (2013) notion of questionnaire data being helpful for rough reviews of a population's refractive problems and to gain important, additional insights. On first sight, the myopia prevalence figures from the present questionnaire study, as well as those from the KiGGS study (Schuster et al., 2020), align well with those derived from refractive data (e.g., Study 1; Truckenbrod et al., 2021). However, when considering the rate of uncorrected myopia reported in Study 1, myopia prevalence estimates from questionnaires should be lower, as they do not include uncorrected and/or undiagnosed myopia. As discussed above, we assume that there may be a bias in recruitment and participation for the questionnaire studies. Thus, our data indicates that one should be careful to use such questionnaire data for "absolute" prevalence estimations. It can, however, be very useful to monitor prevalence development over time, provided the methods between times of data collection or investigations are comparable. One example for this is the KiGGS data on myopia from the baseline study (2003-2006) and wave 2 (2014-2017; Schuster et al., 2020).

2.3.4.4. Relations Within the Questionnaire Data

Another aspect that can be analyzed nicely within data such as the present, and which can probably also be compared between studies with different methodologies, are relations within the data – so long as one can assume that any potential biases in the data or influence of varying methodology do not differ between relevant subsamples. Some of these aspects will briefly be described in the following. As anticipated, our data shows an increased prevalence of spectacle ownership with increasing age. This seems to be primarily driven by changes in myopia prevalence, which is 0.5% in 0-2-year-olds and continuously increases with age, reaching 26.5% among 15-17-year-olds. Consistent with school myopia being described to typically initially appear around the ages 9-11 (Gilmartin, 2004) or 8-14 years (Morgan & Rose, 2005), there is a particularly pronounced rise in myopia prevalence between the age groups of 9-11 and 12-14 years. These results are in line with earlier findings (Rudnicka et al., 2016). Furthermore, we replicate typical findings regarding myopia prevalence regarding

girls and boys: In the overall sample, females consistently exhibit a higher prevalence of spectacles than males, and with regard to the reasons for spectacle ownership, this difference is primarily present for myopia. Concerning age, the prevalence difference between females and males is present in all age groups except for the 3-5-year-olds. It also generally becomes more pronounced with increasing age, with the exception that it is higher in the 9-11-year-old age group than in the older age groups. As mentioned before, these patterns also align with prior literature (Rudnicka et al., 2016).

2.3.4.5. Aspects Related to Eye Health Care

Assessing aspects related to eye health care from the long questionnaire, we discovered that all but two of the 34 spectacle-owning children reported upon had had their spectacles' values assessed by an eye health professional not more than a year ago, the majority even within the last half year. These regular assessments of spectacle fit are promising. Furthermore, their timing seems – for most children – in line with, e.g., the AOA's general recommended schedule for comprehensive eye exams, including one exam at 6-12 months, at least one at 3-5 years, one prior school entry, and then annual exams for all children who are asymptomatic or at low risk of developing eye or vision problems. For at risk children, the alternative of different assessment periods as recommended is added (American Optometric Association, n.d.). Comparably, in Germany, parents of children with spectacles are encouraged to take their child to control examinations at intervals specified by the ophthalmologist (Berufsverband der Augenärzte Deutschlands e.V. & Deutsche Ophthalmologische Gesellschaft e.V., 2007). Of all spectacle-free children from the long questionnaire, 77.5% had at least one assessment about the potential need of spectacles. For most of them, the last one had taken place within the last two years. The majority of the sample having had at least one assessment sounds promising – but 22.5% of the sample never having been assessed is concerning, especially in light of the above-reported recommendations. In the age groups of 6-8 years and upwards, the prevalence of children with at least one assessment is > 90%, and for those aged 9-11 years and above, it even is > 95% – which is especially positive with regard to school myopia onset (Gilmartin, 2004; Morgan & Rose, 2005). Yet, the AOA recommendations include an annual exam for children within these age groups (American Optometric Association, n.d.), and only about 36% per age group of those aged 9-11 years and above had had an exam within the last year. Interestingly, in Germany, for people aged 7-39 years without complaints, ametropia, eye disease or known risk factors for the latter two, recommendations for visual check-ups only include one assessment prior age 16, and then ca. every 10 years (Berufsverband der Augenärzte Deutschlands e.V. & Deutsche Ophthalmologische Gesellschaft e.V., 1998). With

regard to school myopia development and in light of the high rates of uncorrected myopia that we e.g. found in Study 1, one might call this recommendation into question.

This data provides interesting insights into eye health care aspects, though some potential issues should be considered. For one, we asked whether a need for spectacles had ever been assessed. We believed this to be easier to understand than asking about general eye exams, because parents might be unsure what exactly the latter includes. We assumed that comprehensive eye exams would be deemed exams to assess the need for spectacles. Yet, it is possible that some participants did not report an eye examination if the child potentially getting spectacles was not a main concern – i.e., the wording in the questionnaire may have been understood as an assessment following an indication regarding potential spectacle need. We do not suspect this to have been a large issue, because such an indication would primarily be vision problems, which were only reported for 31 of the 307 spectacle-free children, for 30 of which a past eye examination was indicated. Nonetheless, it may be helpful to specify this in a future questionnaire. Furthermore, it is possible that this data from the long questionnaire overestimates the frequency of vision of spectacle assessments in the general public – for example, parents who have their children's spectacles assessed regularly might also more likely be aware of the location of the eyeglass prescription needed to fill in the long questionnaire, and thus more inclined to do so than parents of spectacle-owning children who are assessed less regularly. Likewise, an underestimation of the frequency of assessments is also conceivable: As data acquisition was conducted during the Covid-19 pandemic, parents might have taken their children to fewer assessments than usual, since they might have forgone appointments that they did not deem absolutely necessary or time-sensitive. Thus, such investigations should be repeated post-pandemic.

2.3.4.6. Conclusion and Outlook

Our study reveals a spectacle ownership prevalence of 22.2% among under 18-year-olds in Germany, with the majority attributable to myopia (11.6%). However, when compared to refractive data, it becomes apparent that obtaining absolute prevalence rates from questionnaires presents difficulties. As of now, our considerations regarding the reasons for the apparent mismatch between questionnaire and refractive data are largely speculative. It may be worthwhile to assess this in more detail. Despite all this, questionnaire data seems well-suited for monitoring changes in prevalence over time and for assessing relationships within a sample, as illustrated by our successful replication of typical age- and gender-related patterns in myopia prevalence. Said replication as well as the similarity of our results to those from the KiGGS study (Schuster et al., 2020) suggest that our questionnaire was, to the extent possible for questionnaires, suitable for capturing such data – despite few control over the participants and not accounting for potential overrepresentation of certain demographic

criteria in the data, both being limitations of the present study. Cautious consideration is warranted with regard to comparisons to Schuster et al. (2020), as it is theoretically possible that the myopia prevalence has indeed changed, but our questionnaire did not capture this change due to differences to the one from the KiGGS study (Schuster et al., 2020). However, Schuster et al. (2020) having already found a stable myopia prevalence in children and adolescents in Germany between the KiGGS surveys of 2003-2006 and 2014-2017 supports the notion that our findings may indeed be valid. Furthermore, despite recognizing this thought as circular reasoning – due to the similarity of Schuster et al.'s (2020) and our data being interpreted as support for our questionnaire's suitability –, it is also noteworthy that our data may suggest a stable myopia prevalence in children and adolescents in Germany over the last few years as well. To substantiate this suggestion while avoiding circular reasoning, a repeated questionnaire study with similar methodology as, e.g., the present one conducted in a few years would ideally be needed. Generally, it would be especially interesting to monitor myopia prevalence development in children and adolescents over the next few years, as there may be effects of the Covid-19 pandemic. One recent meta-analysis e.g. found increased annual myopic progression in children and adolescents during compared to prior the Covid-19 pandemic (Watcharapalakorn et al., 2022). Also, aspects of eye health care should be investigated more in the future. Our data suggests that spectacle-owning children received eye health care in an adequate frequency, while the situation could be better for spectacle-free children – although several limitations limit the informative value of the respective data. Overall, while our data provides interesting findings with regard to myopia prevalence development and the usefulness of questionnaire data in this field of research, future research is warranted to expand upon the present findings.

2.3.5. Acknowledgements

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3. Part II

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Methodological Insights Into Light-Myopia Research in Humans Using Wearable Light Meters

3.1. Study 4:

Using Light Meters to Investigate the Light-Myopia Association – A Literature Review of Devices and Research Methods

Abstract: With the increasing prevalence of myopia, evaluating its relationship with objective light exposure as a potential adjustable environmental factor in myopia development has been an emerging research field in recent years. From a thorough literature search, we identify ten wearable light meters from human studies on light exposure and myopia and present an overview of their parameters, thereby demonstrating the wide between-device variability and discussing its implications. We further identify 20 publications, including two reanalyses, reporting investigations of light-myopia associations with data from human subjects wearing light meters. We thoroughly review the publications with respect to general characteristics, aspects of data collection, participant population, as well as data analysis and interpretation, and also assess potential patterns regarding the absence or presence of light-myopia associations in their results. In doing so, we highlight areas in which more research is needed as well as several aspects that warrant consideration in the study of light exposure and myopia.

This study is joint work with Sarah Weigelt, and is published as an article in Clinical Ophthalmology (2023:17, pp. 2737-2760, https://doi.org/10.2147/OPTH.S420631). It has been reformatted to conform to the overall style of this dissertation.

3.1.1. Introduction

The increasing prevalence of myopia worldwide is a cause for concern (Holden et al., 2016). Growing evidence suggests time outdoors (Karthikeyan et al., 2022) and light exposure (Muralidharan et al., 2021) as adjustable environmental factors in myopia development. Hence, assessing the relationship between myopia and light exposure has been an emerging research field in the past years, regarding both animal (Biswas et al., 2023; Karouta & Ashby, 2015) and human (Mirhajianmoghadam et al., 2021; Read et al., 2014, 2015) studies. In human research, objective light measures are often also used to quantify time spent indoors vs outdoors. Thereby, myopia or associated metrics have repeatedly been associated with reduced light and/or outdoor exposure (Mirhajianmoghadam et al., 2021; Read et al., 2014, 2015; Wu et al., 2018). Furthermore, intervention trials increasing children's outdoor exposure found reduced myopia increase in the intervention groups (M. He et al., 2015; Wu et al., 2013; Wu et al., 2018). However, the current evidence is not unambiguous, as some investigations fail to detect associations between light exposure and myopia (Dharani et al., 2012; M. Li et al., 2021). Furthermore, many aspects are still unknown, e.g., whether increased outdoor exposure affects both incidence and progression of myopia and which exact mechanisms underly the protective effect of outdoor exposure (Morgan et al., 2021). While there is strong evidence for bright light as a key protective factor by inhibiting axial elongation through stimulation of retinal dopamine, there also are other hypotheses such as the involvement of vitamin D levels or the impact of different spatial frequencies or spectral composition of light indoors vs outdoors (Morgan et al., 2021). Thus, further research on the association between myopia and light exposure is warranted.

Multiple studies on the association between objectively measured light exposure and myopia in humans have been conducted using various wearable light meters. These studies are subject to great variability, both regarding light meter specifications as well as research methods, and it is important to take this variability into account when assessing and comparing them. Apart from (1) general study characteristics like time of publication, considerations regarding research methods may concern (2) data acquisition, (3) parameters of the participant population, and (4) data analysis and interpretation. In the following, we will briefly review empirical findings on some aspects regarding (2)-(4).

(2) Regarding data acquisition, differences in light measurements from simultaneously worn, different light meters have been shown before (Bhandari et al., 2021; Figueiro et al., 2013; Read, Vincent, et al., 2018). These differences are likely a combination of the devices' specifications as well as how they were worn. The former claim is based on findings showing that deviations in light measurements between light meters and calibrated photometers vary between different types of light meters (Figueiro et al., 2013; Howell et al., 2021; Joyce et al., 2020). This is not surprising since the light meters differ in several aspects,

e.g., spectral sensitivity or measurement range. With regard to device positioning, prior investigations revealed varying degrees of deviation between similar devices worn at different body positions (Aarts et al., 2017; Figueiro et al., 2013; Wen et al., 2021).

Furthermore, the light meters' settings may affect the outcome. Ulaganathan et al. (2017) systematically reduced the measurement duration and coarsened the sampling interval of instantaneous light measurements. They found a significant increase in the measurement variability of outdoor light exposure (daily time exposed to > 1,000 lux), but not group mean light exposure, when fewer measuring days or a coarser sampling interval were analyzed, and concluded that measuring for at least one week and at least every 2 minutes provided the most reliable outdoor light exposure measures (Ulaganathan et al., 2017). Geographical location and season of course also vary between investigations, and, e.g., data acquisition during short daylengths, bad weather and low bright light availability may pose limited opportunities for investigations on associations between light/outdoor exposure and myopia (Flanagan et al., 2020). Any combination of these and other factors provides own challenges, e.g., in choosing the optimal light meter.

(3) One relevant aspect of the participant population is participant age. Since myopia development differs across the lifespan, with school age as a critical period for development and onset of axial myopia (Morgan & Rose, 2005), light exposure probably does not affect it in the same way across all ages. Another aspect is the overall light exposure. There has been speculation that a sample's overall low (frequency of bright) light exposure may conceal associations between light exposure and, e.g., refractive status (Flanagan et al., 2020; Read et al., 2014). Also, Gordon-Shaag et al. (2021) revealed greater myopia prevalence in ultra-Orthodox and religious than secular Israeli boys, but no group differences in outdoor (> 1,000 lux) exposure. They proposed a ceiling effect in the protective effect of outdoor exposure due to high light exposure across all participants, thus explaining the absent associations (Gordon-Shaag et al., 2021). Between-publication variability regarding refractive status assessment and refractive error classification might also be of relevance, as, e.g., outcome differences between several methods to measure refraction have repeatedly been shown (Grzybowski et al., 2020; Hashemi et al., 2016; Rudnicka et al., 2016).

(4) Finally, one major aspect regarding data analysis and interpretation is the calculation of time spent in indoor and outdoor environments. This is often done by quantifying the time spent in light intensities below and above a certain value, usually 1,000 lux (Dharani et al., 2012; M. Li et al., 2021; Mirhajianmoghadam et al., 2021; Read et al., 2014). This indoor-outdoor-cut-off (IO-cut-off) is also frequently used in other research involving personal light exposure (Esaki et al., 2019; L. Liu et al., 2005; Scheuermaier et al., 2010). In myopia research, it has been applied in various circumstances – often without prior validation –, though there are indications that it may not always be the best estimator. For

example, Mahroo et al. (2013) suggested a higher IO-cut-off for a study by Dharani et al. (2012) – who had initially used 1,000 lux, but agreed that 1,500 lux was indeed a better choice for their study (Dharani et al., 2013). With regard to the light meters' specifications, comparability of the IO-cut-off has, e.g., been shown for two different, simultaneously worn devices (Actiwatch 2 and HOBO Temp/Light data logger; Read, Vincent, et al., 2018). However, the previously mentioned findings of different devices' light measurements differently deviating from calibrated photometers alone indicate a high probability of different ideal IO-cut-offs. For two devices, Howell et al. (2021) empirically derived 533.15 lux (Actiwatch 2) and 850 lux (Clouclip) as corresponding to 1,000 lux measured by a photometer. They further remarked that with a 1,000 lux IO-cut-off, the photometer and Clouclip sometimes falsely classified indoors as outdoors, which was almost never the case for Actiwatch 2, due to its general underestimation of illumination (Howell et al., 2021).

These and more aspects pose important challenges for comparing and integrating results of studies on the association between myopia and light/outdoor exposure. Thus, the purpose of this review is to give an overview of the parameters of the wearable light meters used in research on myopia and light/outdoor exposure and the publications investigating associations between them, as well as to reflect upon potential sources of variance between these studies. While there is also research on associations between dim light exposure and myopia (Landis et al., 2018), here, the term "light-myopia associations" (LMA) will be used to describe negative association between bright light and myopia – i.e., more bright light exposure being associated with reduced myopia (metrics). Furthermore, while other factors may (also) underlie the protective effect of bright light/outdoor exposure on myopia (Morgan et al., 2021), we focused on the measurement of (white) light intensity (lux). We hope that this work proves helpful in identifying relevant aspects when assessing or planning research on LMA.

3.1.2. Materials and Methods

3.1.2.1. Literature Search

In the literature search, all publications (journal articles, conference abstracts and posters, dissertations) using light measures with wearable light meters were included. If usage of a light meter, but no measurement or assessment of light was reported, and the device was already included, a publication was not included. The following steps were taken in the literature search: (a) 15 keyword searches were conducted in the PubMed database (see Supplementary Table C1), (b) the reference lists of the identified publications, and then again of the newly identified publications were searched, (c) publications from other sources like the own literature collection were included, and (d) a keyword search for (myopi*) AND (light)

in Web of Science was conducted. For all N = 147 publications identified so far, (e) light meters that had been or may be used in research on light and myopia were extracted (see Supplementary Table C2). For each identified device, a keyword search for ([device name]) AND (myopi*) was conducted in PubMed and Web of Science. Furthermore, (f) a "cited references" search was conducted in Web of Science for all identified publications, in which wearable light meters had been used in combination with myopia research. Finally, (a) and (d) as well as (f) – for the N = 19 publications included in the analysis of research methods (see below) at that point – were repeated in January 2023 to include publications published up to and including 2022. In total, the literature search led to N = 169 publications. These were then assessed regarding their inclusion (see below). Figure 3.1 depicts a flowchart of the literature search, presenting the number of identified, in- and excluded publications.

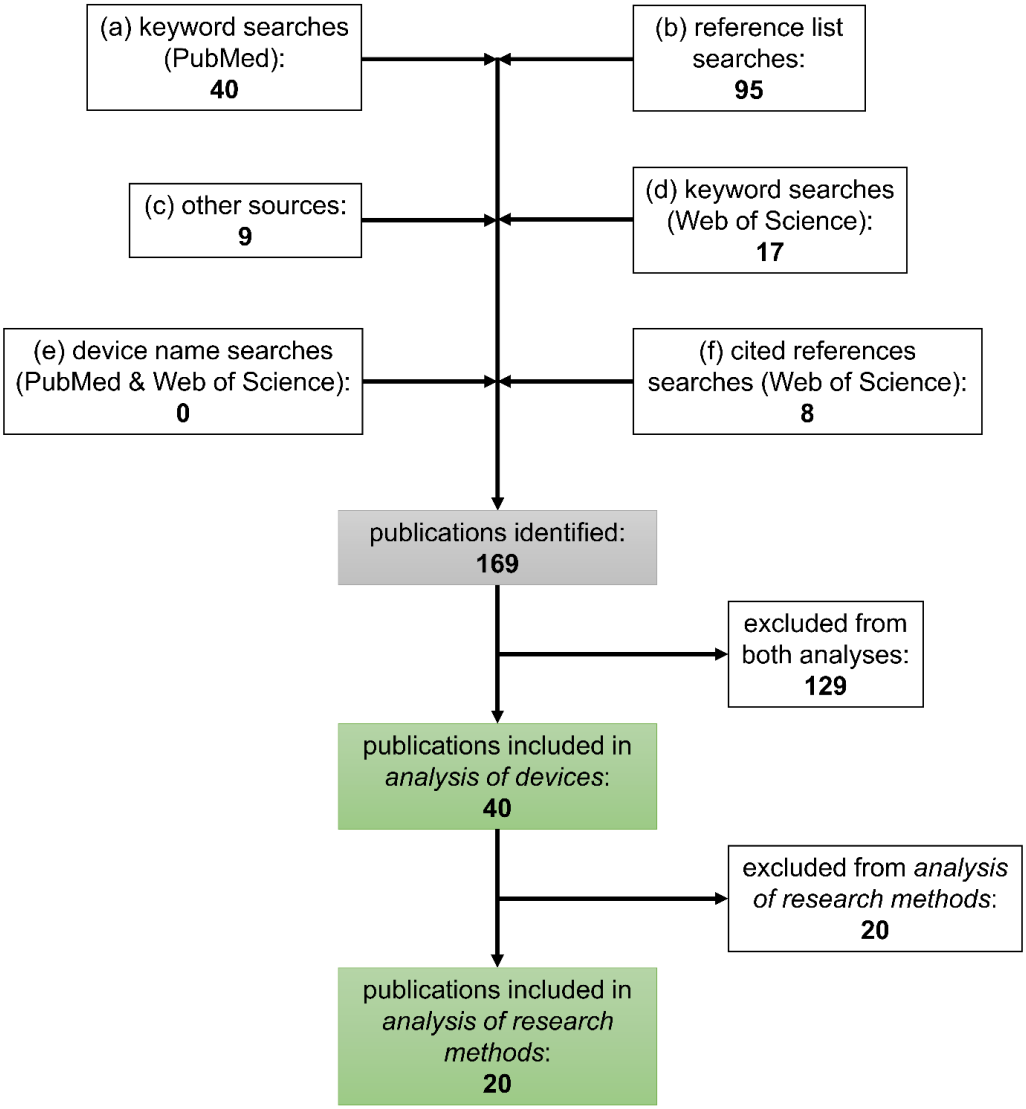


Figure 3.1. Flowchart of the literature search. The numbers indicate how many new publications were identified with the respective search strategies.

3.1.2.2. Inclusion and Exclusion Criteria

Only English sources were considered. Inclusion criteria for the analysis of devices were as follows: (1) paper published in a scientific journal, dissertation, or conference poster – conference abstracts only if the device was not included via one of the former sources; (2) human participants wearing light meters; (3) myopia as a topic of the publication, including methodological investigations; (4) lux data collected, but not necessarily analyzed at all or in direct relation to myopia. If the same data was presented in a conference abstract and a paper, dissertation or conference poster, the conference abstract was excluded. For the analysis of research methods, the following inclusion criteria were applied: (1) paper published in a scientific journal, dissertation, or conference poster; (2) human participants wearing light meters; (3) myopia as a topic of the publication; (4a) lux data analyzed as a main outcome and in direct relation to refractive error/ myopia/a proxy metric like axial length OR (4b) methodological investigation within the framework of wearable sensors in light exposure-myopia research, also reporting results on the association between (white) light intensity (lux) and refractive error/myopia (metrics). Due to criteria 4a and 4b, publications primarily concerned with other associations (e.g., myopia – circadian rhythm), in which the relation between (white) light intensity and myopia was also analyzed, were not included because we assumed that their methodology would have been optimized for assessing their main objective rather than LMA. In one case, a study within a dissertation (Alvarez, 2012) was later published in a paper (Alvarez & Wildsoet, 2013), and both were identified in the literature search. Since methods, analyses and results on light exposure and refractive error appear to be similar in both publications, we only included the paper. Another publication did not fit criterion 4a perfectly as the analyses on LMA were not a main focus. However, as the investigation assessed an intervention to increase light exposure and time outdoors for myopia control and not other associations with light exposure and myopia, and analyses on LMA were conducted, it was included (S.-M. Li et al., 2022).

3.1.3. Results

3.1.3.1. Analysis of Devices

We identified ten wearable light meters from human studies on light exposure and myopia based on 40 publications. As stated above, this review focuses on the association between myopia and light intensity measured in lux – the measurement unit of illuminance. Illuminance is defined as irradiance weighed by the photopic luminous efficiency function V(λ), which is based on the spectral sensitivity of human central vision, if not specified to follow another luminous efficiency function (Figueiro et al., 2013; Ohno et al., 2020). However, in practice, the devices' illuminance estimation is not always accurate, as, e.g., their

spectral sensitivity may deviate from V(λ) (Figueiro et al., 2013; Joyce et al., 2020). This should be kept in mind regarding the terminology used to describe the devices' light measurement capacities.

In the following, all identified devices will be described briefly, together with a list of the associated publications. More detailed information is presented in Table 3.1. The information provided in the publications and by the manufacturers did not always contain all relevant details for our descriptions. Where possible, we asked authors and/or manufacturers for the respective details. If we could not receive the information, we consulted further sources, e.g., other publications. If we could still not get the respective information, or it was conflicting between different sources, n/a is stated in the table. Also, while monetary aspects are certainly relevant for planning investigations, they are not included here. Furthermore, not all devices are commercially available (anymore), the reported specifications may change without notice, and devices used in cited publications might have had different specifications than reported here, e.g., if an earlier version was used.

The Actiwatch 2 (Philips Respironics, Murrysville, PA, USA; Flanagan et al., 2020; Franklin, 2020; Landis et al., 2018; Ostrin et al., 2020; Read et al., 2014, 2015; Read, Pieterse, et al., 2018; Read, Vincent, et al., 2018; Ulaganathan et al., 2019a, 2019b) is a wrist-worn actigraphy device. It includes a solid-state "piezo-electric" accelerometer sampling at 32 Hz and a silicone photodiode light sensor, and measures activity and photopic illuminance (lux). Events can be recorded via button press (Koninklijke Philips N.V., n.d.–a).

The Actiwatch Spectrum (Philips Respironics, Murrysville, PA, USA; Abbott et al., 2018; Burfield et al., 2019; Gordon-Shaag et al., 2021; Ostrin, 2017; Ostrin et al., 2018; Ostrin, 2018; Ostrin et al., 2019; Shneor et al., 2021; R. Williams et al., 2019) is a wrist-watch and activity monitor. It is also equipped with a solid-state "piezo-electric" accelerometer sampling at 32 Hz to record activity, and an event marker button. Light, however, is measured via three (red, green, blue) color-sensitive photodiodes, and available light measurement units are irradiance (μW/cm²), photon flux (photons/cm²/s), and photopic illuminance (lux). Furthermore, the device has an off-wrist detector (Koninklijke Philips N.V., n.d.–b). Following its production stop, the Actiwatch Spectrum Plus and PRO were its successor models.

The Actiwatch Spectrum Plus (Philips Respironics, Murrysville, PA, USA; Bhandari et al., 2021; Mirhajianmoghadam et al., 2021) is a wrist-watch and activity monitor with many features like off-wrist detection, an event marker button, and light measurements similar to the Actiwatch Spectrum. Activity is also sampled at 32 Hz, but via an MEMS type accelerometer (Koninklijke Philips N.V., n.d.–c).

The Actiwatch Spectrum PRO (Philips Respironics, Murrysville, PA, USA; Harb et al., 2016) includes the same features as the Actiwatch Spectrum Plus and additionally provides

the option to record two subjective scores (manually or on a programmed schedule) and alarms to remind participants to enter them (Koninklijke Philips N.V., 2013).

The Clouclip (Hangzhou JingZhiJing Technology Co. Ltd., Hangzhou, China; Bhandari et al., 2021; Bhandari et al., 2022; L. Li et al., 2020; L. Li et al., 2021; Wen et al., 2019; Wen et al., 2020; Wen et al., 2021) is a small device clipped to the right side of spectacles. It can measure viewing distance and duration via a laser ranging module, illuminance (lux) via an illuminance monitoring module, and viewing angle via a three-axis accelerometer (Bhandari et al., 2021; Hangzhou JingZhiJing Technology Co. Ltd., n.d.). Two versions with partially different features are internationally available for personal use (Clouclip P2) and for business and research purposes (Clouclip M2; Hangzhou JingZhiJing Technology Co. Ltd., n.d.), though similar sensors are used in both (Hangzhou JingZhiJing Technology Co. Ltd., personal communication, 2022). If no movement is detected for 40 seconds, Clouclip M2 goes into sleep mode until movement is detected again, but for at least 2 minutes (Bhandari et al., 2021). Clouclip P2 goes into sleep mode after 10–20 seconds without movement (Hangzhou JingZhiJing Technology Co. Ltd., personal communication, 2022).

The FitSight fitness tracker (patent WO2015152818A1; M. Li et al., 2021; Saw et al., 2015; Verkicharla et al., 2017) was developed by researchers (Verkicharla et al., 2017) to record, quantify, indicate, and motivate daytime outdoor activity. It includes a smart watch with a custom-made app and a smartphone app, and records ambient light illuminance (lux). The smart watch app also consists of an accelerometer function. Time outdoors is calculated by summarizing the time spent above an illumination threshold and via Bluetooth, this information is relayed to the smartphone app. A congratulatory message for reaching the daily outdoor time target and motivational messages if the target is not reached at specific times can be presented. One can also monitor physical activity in 30-minute epochs (Verkicharla et al., 2017).

The HOBO Pendant Temp/Light data logger (Onset Computer Corp., Bourne, MA, USA; Alvarez & Wildsoet, 2013; Backhouse et al., 2011; Dharani et al., 2012; S.-M. Li et al., 2022; Moafa, 2019; Read, Vincent, et al., 2018; Schmid et al., 2013; Wu et al., 2018) is a small logger recording temperature and light intensity (lux) readings. Two versions have been used in the identified publications, the HOBO Pendant UA-002-64 and the HOBO Pendant UA-002-08, which only differ in their memory capacity (64 KB vs 8 KB; Onset Computer Corporation, 2012).

The Mumu (X. He et al., 2019; X. He et al., 2022; Ye et al., 2019), developed by researchers (Ye et al., 2019), is a smart watch containing a light sensor, a three axis-accelerometer, and a GPS receiver. It can sample illuminance (lux) and ultraviolet (UV) intensity, steps, and location data. Furthermore, weather and temperature can be synchronized in real time, and weather information is sampled as sunny/cloudy. Wearing

status can be determined through light sensors in both front and back of the watch (Ye et al., 2019). Parents can manage the device via an app (X. He et al., 2019), and there is a website portal for teachers so that they, e.g., can intervene if students wear the device improperly. A next generation, more lightweight device with longer battery life has also been developed and will eventually be put on the market (Xiangui He, personal communication, 2022).

The MyLyt (Dhakal et al., 2023) is a prototype developed at the LV Prasad Eye Institute (Hyderabad, India) to track real-time light exposure. It records illumination (lux) against real time. A light-emitting diode can indicate data sampling (green) and low battery (red). Further improvements, e.g., a smartphone connection for data transfer or reducing size and weight, are planned (Dhakal et al., 2023).

The Vivior Monitor (Vivior AG, Zurich, Switzerland; Tanrıverdi et al., 2019, April 28-May 2) is small device clipped to the right side of spectacles via an adapter. It encompasses two optical time-of-flight distance sensors directed forward and 30° downward, an ambient light sensor with separate red, green, blue and infrared channels directed forward, a combined UV and ambient light sensor directed upward, as well as motion and orientation sensors (accelerometer, gyroscope, magnetometer). Thus, the device can record various parameters, like viewing distance, head rotation, illuminance (lux), exposure to red, green, and blue light, and UV exposure. The illuminance measure is derived from the forward-oriented sensor as a mixture of the channels. Currently, the upwards-oriented light sensor is mainly used to quantify UV exposure (Vivior AG, n. d.). The device starts measuring when attached to the adapter, and stops when detached or when the spectacles are taken off (Pajic et al., 2020) It can be used to create viewing profiles with recommendations for glasses and viewing behavior.

Additionally, we identified the Akeso eye care glasses (Beijing Akeso Technology Co., Ltd., Beijing, China; Fan et al., 2022), which have sensors installed in the right spectacle arm and contain a six-axis sensor, an UV light sensor, and a proximity sensor. Time of wearing, being outdoors, and near viewing can be recorded (Fan et al., 2022). Fan et al. (2022) describe UV ≥ 1 or lux ≥ 1,500 to be recognized as outdoors, and UV < 1 or lux < 1,500 as indoors. We could not determine if the device can provide lux data, or if lux is only used to determine outdoor time. Thus, the device is not included in Table 3.1.

In summary, researching and developing devices to measure light exposure in the context of myopia is a rapidly developing field of research, and several other devices are being or have recently been developed, e.g., the LUMINO-SD (Nishanth et al., 2022). Furthermore, there are a number of other light meters that could theoretically be used for such research. Hartmeyer et al. (2022) present an overview of light dosimeters used in previous studies on non-visual effects of light.

Table 3.1

Overview of the Identified Devices

device	kind of device[a]	available light measurements[b]	lux measurement range	spectral sensitivity of light sensor(s)	light sampling & logging interval[c]
Actiwatch 2 (Koninklijke Philips N.V., n.d.–a, 2019)	wrist-worn device	**photopic illuminance (lux)**	5-100,000 lux	range: 400-900 nm peak: 570 nm	instantaneous[d] light measurement with possible logging frequencies of 15 s, 30 s, 1 min, 2 min, and 5 min
Actiwatch Spectrum (Figueiro et al., 2013; Gordon-Shaag et al., 2021; Koninklijke Philips N.V., n.d.–b, 2008; Ostrin, 2017; Ostrin et al., 2018; Udovičić et al., 2016)	wrist-worn device	**photopic illuminance (lux)** irradiance photon flux	1–100,000 lux (Udovičić et al., 2016) / 0.1-200,000 lux (Gordon-Shaag et al., 2021; Ostrin, 2017; Ostrin et al., 2018)	range: 400-700 nm peak: ca. 510 nm	possible logging frequencies 15 s, 30 s, 1 min, 2 min & 5 min, averaged from shorter sampling interval[e]
Actiwatch Spectrum Plus (Koninklijke Philips N.V., n.d.–c, 2019)	wrist-worn device	**photopic illuminance (lux)** irradiance photon flux	n/a	range: 400-700 nm (Koninklijke Philips N.V., n.d.–c) / 380-750 nm (Koninklijke Philips N.V., 2019) peak: n/a	possible logging frequencies 15 s, 30 s, 1 min, 2 min & 5 min, averaged from shorter sampling interval[e]
Actiwatch Spectrum PRO (Koninklijke Philips N.V., n.d.–d, 2019)	wrist-worn device	**photopic illuminance (lux)** irradiance photon flux	n/a	range: 400-700 nm (Koninklijke Philips N.V., n.d.–d) / 380-750 nm (Koninklijke Philips N.V., 2019) peak: n/a	possible logging frequencies 15 s, 30 s, 1 min, 2 min & 5 min, averaged from shorter sampling interval[e]

Table 3.1 – Continued

Overview of the Identified Devices

Clouclip (Bhandari et al., 2021)	glasses clip	**illuminance (lux)**	1-65,528 lux	range: ca. 400-760 nm peak: ca. 540 nm	logged every 2 min, averaged from shorter sampling frequency
FitSight[f] (Sony Mobile Communications Inc., 2014; Verkicharla et al., 2017)	wrist-worn smart watch	**illuminance (lux)**	n/a	n/a	recorded at 1-min intervals, sampling frequency n/a
HOBO Pendant Temp/Light data logger (Onset Computer Corporation, 2012)	encapsulated logger	**light intensity (lux)**	0-320,000 lux	range: ca. 150-1,200 nm peak: ca. 900 nm	instantaneous light measurement with freely configurable logging frequency from 1 s onward
Mumu (Silicon Labs, 2014; Ye et al., 2019)	wrist-worn smart watch	**illuminance (lux)** UV intensity	1-128,000 lux (possible; light sensor has dynamic range)	range: ca. 290-1,060 nm peak: ca. 450 nm	instantaneous light intensity measured every 20 s, sampling every 1 min – but 3 data points sampled every 1 min for the light measurements
MyLyt (Dhakal et al., 2023)	clip-on encapsulated logger	**illuminance (lux)**	0-88,000 lux	range: 400-850 nm peak: ca. 600-655 nm	instantaneous light measurement with freely configurable logging frequency from 1 s onward

Table 3.1 – Continued

Overview of the Identified Devices

Vivior Monitor (Vivior AG, n. d.)	glasses clip	**illuminance (lux)** red, green, blue components of visible ambient light as well as infrared channel ambient light color temperature UV exposure	0-100,000 lux (graphical display 0-10,000 lux, export and statistics include full range)	range: ca. 360-1,100 nm (forward oriented sensor – all channels), 400-800 nm (forward oriented sensor – lux estimation), peak: ca. 530 nm (forward oriented sensor – lux estimation)	per default logged every 5 min, averaged from 0.5 s sampling frequency; higher data granularity available upon request for research purposes

Table 3.1 – Continued

Overview of the Identified Devices

device	size & weight	battery	initialization, data accessibility & storage	water resistance	nighttime wearability
Actiwatch 2 (Koninklijke Philips N.V., n.d.–a, 2019)	size: 43 x 23 x 10 mm weight: 16 g	rechargeable lithium cell battery; 30 days typical battery life with 1 min epoch (activity and light measurements); communication dock needed for charging	communication dock and software needed for device initialization and data access; data access via software on a computer	waterproof at 1 m for 30 min (per IPX7 IEC 60529)	yes
Actiwatch Spectrum (Figueiro et al., 2013; Gordon-Shaag et al., 2021; Koninklijke Philips N.V., n.d.–b, 2008; Ostrin, 2017; Ostrin et al., 2018; Udovičić et al., 2016)	size: 48 x 37 x 14 mm weight: 30 g	non-rechargeable CR 2430 Lithium Coin Cell; needs to be returned to manufacturer for replacement; 8 months battery life with continuous use	communication dock and software needed for device initialization and data access; data access via software on a computer	waterproof at 1 m for 30 min (per IPX7 IEC 60529)	yes

Table 3.1 – Continued

Overview of the Identified Devices

Actiwatch Spectrum Plus (Koninklijke Philips N.V., n.d.–c, 2019)	size: 48 x 37 x 15 mm weight: 31 g	rechargeable lithium ion battery; 60 days typical battery life with 1 min epoch (activity and light measurements); charging via Micro-USB port	software needed for device initialization and data access; data access via software on computer	waterproof at 1 m for 30 min (per IPX7 IEC 60529)	yes
Actiwatch Spectrum PRO (Koninklijke Philips N.V., n.d.–d, 2019)	size: 48 x 37 x 15 mm weight: 31 g	rechargeable lithium ion battery; 50 days typical battery life with 1 min epoch (activity and light measurements + 4 daily scores/alarms); charging via Micro USB port	software needed for device initialization and data access; data access via software on computer	waterproof at 1 m for 30 min (per IPX7 IEC 60529)	yes
Clouclip (Bhandari et al., 2021)	size: 45 x 13 x 8 mm weight: 5 g	rechargeable lithium polymer battery; average battery life ca. 35 h; charging via cable, magnetically attached to the device, with USB plug on other end	smartphone app and Bluetooth connection needed for device initialization and data upload; after data acquisition, data uploaded to online database via the app	splashproof	no: device worn on glasses and needs overnight charging if worn for multiple days

Table 3.1 – Continued

Overview of the Identified Devices

FitSight[f] (Sony Mobile Communications Inc., 2014; Verkicharla et al., 2017)	n/a	Sony Smartwatch 3 battery rechargeable via Mini USB	n/a	Sony Smartwatch 3 waterproof at 1.5 m for 30 min (per IP68)	yes (provided that the battery life is sufficient)
HOBO Pendant Temp/Light data logger (Onset Computer Corporation, 2012)	size: 48 x 33 x 23 mm weight: 18 g	changeable battery (3-Volt CR-2032 lithium battery); typically lasts 1 year with logging intervals > 1 min; with continuous logging at fastest rate (1 s), battery lasts 2 weeks	optic USB base station, coupler and software needed for device initialization and data access; data access via software on a computer	waterproof (30 m from -20 to 20 °C, 10 m at 50 °C)	problematic: usual wearing options (e.g. as a necklace or pinned to clothing) likely cause discomfort and/or safety issues
Mumu (Silicon Labs, 2014; Ye et al., 2019)	size: 600 x 400 x 200 mm weight: ca. 65 g	rechargeable battery; battery life > 20 h; charging via Mini USB	device automatically starts data acquisition once it is powered on; data is uploaded to a private cloud after data acquisition	splashproof	yes (though battery life may restrict multiple day wear)

Table 3.1 – Continued

Overview of the Identified Devices

MyLyt (Dhakal et al., 2023)	size: 47 x 37 x 16.4 mm weight: 50 g	rechargeable lithium polymer battery; battery life 7 days at a sampling rate of 60 s; charging via USB	automatic device initialization when program is loaded; data is stored manually on a flash memory	splashproof (presently; can be made waterproof per IP67)	problematic: device being pinned on clothing below neck likely to cause discomfort and/or safety issues
Vivior Monitor (Vivior AG, n. d.)	size: 60 x 19 x 14 mm weight: 14 g	rechargeable lithium ion polymer battery (120 mAh capacity); allows for data collection for up to 16 h; charging via standard USB 5V port	PC app needed for device initialization and data access; after data acquisition, data uploaded to Vivior cloud via the app	no	no: device worn on glasses and needs overnight charging if worn for multiple days

Note. The sources of information are noted alongside the device names. Additional information was obtained as follows: Clouclip – Hangzhou JingZhiJing Technology Co. Ltd. (personal communication, 2022, 2023); Mumu – Xiangui He (personal communication, 2022); MyLyt – Pavan Verkicharla (personal communication, 2023); Vivior Monitor – Vivior AG (personal communication, 2022, 2023). [a]That is worn – overall system may include more parts, eg smartphone apps. [b]Labels as stated by manufacturer/ developer. [c]May not apply for all other available measurements of the device. [d]No manufacturer confirmation could be obtained, but other publications (Read et al., 2015; Ulaganathan et al., 2017) and own observations indicate instantaneous measurements. [e]No manufacturer confirmation could be obtained, but other publications (with Actiwatch Spectrum & Spectrum Plus; Bhandari et al., 2021; Mirhajianmoghadam et al., 2021; Ostrin et al., 2017) and own observations with the Actiwatch Spectrum PRO indicate averaging over a shorter sampling interval. The sampling frequency is often stated as 32 Hz for both light & activity data (Bhandari et al., 2021; Ostrin et al., 2017), but on the manufacturer's website, 32 Hz is explicitly given as the accelerometer sampling rate for all Actiwatches, with no indication of the light sampling rate. [f]Verkicharla et al. (2017) state the Sony Smartwatch 3 as being used in the described FitSight version, so some information is based on its specifications.

3.1.3.2. Analysis of Research Methods

We identified 18 journal articles (Alvarez & Wildsoet, 2013; Bhandari et al., 2022; Dharani et al., 2012; X. He et al., 2022; Landis et al., 2018; L. Li et al., 2020; M. Li et al., 2021; S.-M. Li et al., 2022; Mirhajianmoghadam et al., 2021; Ostrin, 2017; Ostrin et al., 2018; Read et al., 2014, 2015; Read, Vincent, et al., 2018; Schmid et al., 2013; Ulaganathan et al., 2019b; Wen et al., 2020; Wu et al., 2018), one dissertation (Franklin, 2020), and one conference poster (Backhouse et al., 2011). A detailed overview on their methodological aspects and findings regarding LMA can be found in Supplementary Table C3. For completeness, publications within a similar context but not fitting the inclusion criteria for this analysis (Abbott et al., 2018; Burfield et al., 2019; Fan et al., 2022; Flanagan et al., 2020; Ostrin, 2018; Tanrıverdi et al., 2019, April 28-May 2) are mentioned in Supplementary Information C1.

In the following, the publications will be assessed regarding selected methodological aspects to illustrate their methodological variety in (1) general characteristics, (2) data acquisition, (3) participant population, and (4) data analysis and interpretation. For the first three topics, we also looked for potential patterns regarding these aspects and the publications' results supporting or not supporting LMA. Usually, no such patterns were observed. This is not surprising, given the large number of factors potentially influencing the results, the small number of publications and the usually large methodological variability. The absence of apparent patterns will thus not be discussed in detail for every aspect, but any interesting discoveries will. Furthermore, it was not attempted to assess such patterns for data analysis and interpretation aspects, since (almost) no grouping of publications in terms of these aspects was possible. Reanalyses (Landis et al., 2018; Read, Vincent, et al., 2018) are not generally included to not give a skewed impression of the data. If they are considered, it is explicitly stated. Lastly, there is a large overlap in the participants of two publications (Read et al., 2014, 2015), but since one is cross- sectional and one primarily longitudinal, they will be considered separately.

3.1.3.2.1. General Characteristics

3.1.3.2.1.1. Time of Publication

To assess potential time trends regarding the publications or results on LMA, we assessed them regarding their time of publication. The oldest publication stems from 2011 (Backhouse et al., 2011), the most recent one from 2022 (S.-M. Li et al., 2022), the last year included in the review. The number of publications has grown more rapidly in more recent years, as six publications were published in the first (Alvarez & Wildsoet, 2013; Backhouse et al., 2011; Dharani et al., 2012; Read et al., 2014, 2015; Schmid et al., 2013), and twelve in the second half of said timeframe (Bhandari et al., 2022; Franklin, 2020; X. He et al., 2022; L. Li et al., 2020; M. Li et al., 2021; S.-M. Li et al., 2022; Mirhajianmoghadam et al., 2021; Ostrin, 2017;

Ostrin et al., 2018; Ulaganathan et al., 2019b; Wen et al., 2020; Wu et al., 2018). Noticeably, the four oldest publications all report no LMA (Alvarez & Wildsoet, 2013; Backhouse et al., 2011; Dharani et al., 2012; Schmid et al., 2013). The other four publications with no or only few such evidence were published later (Franklin, 2020; M. Li et al., 2021; Ostrin, 2017; Ostrin et al., 2018), in between publications supporting LMA. Importantly, the four oldest publications also share other features as will be discussed below. Thus, no clear-cut conclusion can be drawn based on time of publication alone.

3.1.3.2.1.2. Type of Study

Lingham et al. (2020) state that longitudinal, but not cross-sectional studies using light meters found associations between higher average daily light exposure and slower eye growth. This is not reflected in our analysis, as LMA have been found both cross-sectionally and longitudinally. Of the ten cross-sectional publications, five show support for LMA (Bhandari et al., 2022; L. Li et al., 2020; Mirhajianmoghadam et al., 2021; Read et al., 2014; Wen et al., 2020), and five (almost) none (Alvarez & Wildsoet, 2013; Dharani et al., 2012; M. Li et al., 2021; Ostrin, 2017; Schmid et al., 2013). Of the eight longitudinal studies, the respective numbers are five (X. He et al., 2022; S.-M. Li et al., 2022; Read et al., 2015; Ulaganathan et al., 2019b; Wu et al., 2018) and three (Backhouse et al., 2011; Franklin, 2020; Ostrin et al., 2018), though one of the latter longitudinal studies only encompassed three months (Backhouse et al., 2011). Especially considering this, longitudinal publications tend to report LMA more often than cross-sectional ones. However, since one longitudinal publication reporting LMA (Ulaganathan et al., 2019b) and three cross-sectional ones not doing so (Alvarez & Wildsoet, 2013; Ostrin, 2017; Schmid et al., 2013) have adult participants, this pattern does not exist when only considering publications with children.

3.1.3.2.2. Data Acquisition

3.1.3.2.2.1. Measurement Device

As various devices with different specifications (see Table 3.1) have been used to assess LMA, we considered potential associations between devices and wearing positions and results on LMA. The number of publications per device are: HOBO Pendant Temp/Light data logger – six (Alvarez & Wildsoet, 2013; Backhouse et al., 2011; Dharani et al., 2012; S.-M. Li et al., 2022; Schmid et al., 2013; Wu et al., 2018), Actiwatch 2 – four (Franklin, 2020; Read et al., 2014, 2015; Ulaganathan et al., 2019b), Clouclip – three (Bhandari et al., 2022; L. Li et al., 2020; Wen et al., 2020), Actiwatch Spectrum – two (Ostrin, 2017; Ostrin et al., 2018), Actiwatch Spectrum Plus – one (Mirhajianmoghadam et al., 2021), FitSight – one (M. Li et al., 2021), Mumu – one (X. He et al., 2022). No publication with Actiwatch Spectrum PRO, MyLyt or Vivior Monitor fit the inclusion criteria. Of the six HOBO Pendant Temp/Light data logger publications, only two support LMA (S.-M. Li et al., 2022; Wu et al., 2018). A somewhat

reversed pattern emerges for the Actiwatch 2, where three of the four publications support LMA (Read et al., 2014, 2015; Ulaganathan et al., 2019b). The publication with the Actiwatch Spectrum Plus reports results in favor of LMA (Mirhajianmoghadam et al., 2021), while the two publications with the Actiwatch Spectrum either found no (Ostrin, 2017) or only little (Ostrin et al., 2018) support. The publication with Mumu shows strong support (X. He et al., 2022), the one with FitSight only minimal (M. Li et al., 2021). Finally, all three publications with Clouclip strongly support LMA (Bhandari et al., 2022; L. Li et al., 2020; Wen et al., 2020).

The devices used entail differing wearing positions. While the HOBO Pendant Temp/Light data logger is usually worn forward-facing at the chest or collar, it has been mounted on a pedestal facing skyward in one case (Alvarez & Wildsoet, 2013), and one publication does not report its wearing position (Backhouse et al., 2011). Clouclip can only be worn on the right side of spectacles, and all wrist- worn devices were worn as intended in the publications.

While there is no apparent pattern regarding the support of LMA, it is interesting that the HOBO Pendant Temp/Light data logger was used in the four earliest publications, in which no such support was found (Alvarez & Wildsoet, 2013; Backhouse et al., 2011; Dharani et al., 2012; Schmid et al., 2013). Possibly, its technical specifications or ways of wearing may play a role here – though the two more recent publications with this device do report LMA (S.-M. Li et al., 2022; Wu et al., 2018). Furthermore, the publications with Clouclip (Bhandari et al., 2022; L. Li et al., 2020; Wen et al., 2020) are the only ones included that measured eye-level light exposure. All three of them supporting LMA may suggest that relevant differences in light exposure are indeed best uncovered in this manner. Overall, while such hints may suggest specific devices and their wearing location as better suited for identifying LMA, the small number of included publications makes this assessment speculative at this point.

3.1.3.2.2.2. Sampling and Logging Interval

As a measurement frequency (instantaneous sampling) of ≤ 2 minutes has been recommended for reliable ambient light and outdoor exposure measurements (Alvarez & Wildsoet, 2013; Ulaganathan et al., 2017), we reviewed this aspect. Importantly, sampling and logging interval are not always the same – some devices log an averaged value of data sampled at finer intervals. The measurement frequency was consistent with the above recommendation in most publications, with logging intervals between 10 seconds (Alvarez & Wildsoet, 2013; Backhouse et al., 2011; S.-M. Li et al., 2022) and 2 minutes (Bhandari et al., 2022; L. Li et al., 2020; Wen et al., 2020). The underlying sampling interval was sometimes even finer due to averaged logging. There are three publications with instantaneous sampling intervals coarser than 2 minutes – namely 5 minutes –, two of which did not find LMA (Dharani et al., 2012; Schmid et al., 2013), and one did (Wu et al., 2018). Furthermore, Read, Vincent, et al. (2018) resampled data from Read et al. (2014, 2015) at 5 minutes, and still

found significantly lower outdoor light exposure in myopic than non-myopic children in these data. Generally, the absence of an apparent results pattern is not surprising since the recommended measurement frequency (Alvarez & Wildsoet, 2013; Ulaganathan et al., 2017) was almost always fulfilled.

3.1.3.2.2.3. Measurement Duration

Similarly, almost all publications report a measurement duration of seven days or longer, thus laying within the recommended timeframe of ≥ 1 week (Ulaganathan et al., 2017), so the absence of a results pattern is again unsurprising. In one of the two publications with a shorter duration, participants wore the device for 3 days, and no LMA were found (Schmid et al., 2013). In the other one, participants wore the device for 6 days (three before, three after an intervention), and LMA were found (S.-M. Li et al., 2022). All other durations varied between 7 days (Bhandari et al., 2022; Dharani et al., 2012; L. Li et al., 2020; Wen et al., 2020; Wu et al., 2018) and 1 year (X. He et al., 2022).

3.1.3.2.2.4. Geographic Location

The publications' data was acquired in six countries: USA (five; Alvarez & Wildsoet, 2013; Bhandari et al., 2022; Mirhajianmoghadam et al., 2021; Ostrin, 2017; Ostrin et al., 2018), Australia (four; Read et al., 2014, 2015; Schmid et al., 2013; Ulaganathan et al., 2019b), New Zealand (one; Backhouse et al., 2011), China (four; X. He et al., 2022; L. Li et al., 2020; S.-M. Li et al., 2022; Wen et al., 2020), Taiwan (one; Wu et al., 2018), Singapore (two; Dharani et al., 2012; M. Li et al., 2021), and the UK (one; Franklin, 2020). We assumed two locations based on the authors' affiliations (Backhouse et al., 2011; L. Li et al., 2020). Thus, an important result of this analysis is the grave lack of data for many parts of the world. Notably, while there is a high myopia prevalence among school children in both East Asia and Singapore (Ding et al., 2017), all five publications from East Asia (China & Taiwan) report LMA (X. He et al., 2022; L. Li et al., 2020; S.-M. Li et al., 2022; Wen et al., 2020; Wu et al., 2018), but either no (Dharani et al., 2012) or only few (M. Li et al., 2021) LMA were found in both Singaporean publications, all of which were conducted with school-aged children. No other pattern regarding results on LMA was detected.

3.1.3.2.2.5. Season

A relationship between season and myopia development has repeatedly been shown – for example, myopia progression and axial elongation in children is slower in summer than winter, which may be related to children spending more time outdoors during summer (Cui et al., 2013; Donovan et al., 2012; Gwiazda et al., 2014). Season therefore is an important factor that may influence the strength or even presence of LMA. Thus, we assessed the publications in this regard, though this is challenging for multiple reasons. For once, while there are highly distinct seasons at many locations in the world, this is not the case for others.

And even for locations with distinct seasons, aspects like weather or daylength and their between-season differences are highly variable. We did not attempt to assess potential patterns between season and results on LMA, as season is not usually systematically controlled in the publications and many related aspects vary greatly between them: In four publications, no information is available on the season of data acquisition (L. Li et al., 2020; M. Li et al., 2021; Schmid et al., 2013; Wen et al., 2020), and in another four, the analyzed data was acquired during one season (summer – Franklin, 2020; Mirhajianmoghadam et al., 2021, winter – Backhouse et al., 2011, "mild, rainy season" – Dharani et al., 2012). Participants in X. He et al. (2022) wore the device for 1 year, thus covering all seasons. In five further publications, different participants participated in different seasons (Alvarez & Wildsoet, 2013; Bhandari et al., 2022; S.-M. Li et al., 2022; Ostrin, 2017; Read et al., 2014), and in the remaining four, the same participants participated multiple times and across different seasons (Ostrin et al., 2018; Read et al., 2015; Ulaganathan et al., 2019b; Wu et al., 2018) – in both cases, we sometimes presumed this based on measurement periods. While season was analyzed with regard to light exposure in six publications (Alvarez & Wildsoet, 2013; Franklin, 2020; Ostrin, 2017; Ostrin et al., 2018; Read et al., 2015; Ulaganathan et al., 2019b), it was investigated within LMA in only three: One reports seasonal differences on associations between refractive groups as well as axial length and light exposure (Ulaganathan et al., 2019b), one found season-independent light exposure differences between refractive groups (Read et al., 2015), and one detected seasonal light exposure differences, but no effect of refractive groups upon them (Ostrin et al., 2018). Due to the relationship between season and myopia development, the large between-publication variation regarding season of data acquisition and whether it is systematically controlled or even reported should be considered as seasonal differences might influence LMA.

Measurement of refractive status and refractive group classification are also aspects of data acquisition, but they are closely related to aspects regarding the participant population as well, and will be considered in the next paragraph.

3.1.3.2.3. Participant Population

3.1.3.2.3.1. Number of Participants

The publications show large variability in the number of (analyzed) participants, ranging from twelve (Backhouse et al., 2011) to 6,295 (X. He et al., 2022). There may be a tendency for publications with more participants to support LMA more often than not and vice versa: Of the nine publications analyzing more than 80 participants, seven report results in support of LMA (X. He et al., 2022; L. Li et al., 2020; S.-M. Li et al., 2022; Read et al., 2014, 2015; Wen et al., 2020; Wu et al., 2018), and only two show little to no support (Dharani et al., 2012; M. Li et al., 2021). Of the nine publications with fewer than 80 participants, only three present strong (Bhandari et al., 2022; Mirhajianmoghadam et al., 2021; Ulaganathan et al.,

2019b) and six little to no support (Alvarez & Wildsoet, 2013; Backhouse et al., 2011; Franklin, 2020; Ostrin, 2017; Ostrin et al., 2018; Schmid et al., 2013).

3.1.3.2.3.2. Participant Age

Only four publications investigated adult participants (Alvarez & Wildsoet, 2013; Ostrin, 2017; Schmid et al., 2013; Ulaganathan et al., 2019b), while 14 publications studied children. Of the publications targeting adults, only one (Ulaganathan et al., 2019b) supports LMA, while nine of the publications with child data do (Bhandari et al., 2022; X. He et al., 2022; L. Li et al., 2020; S.-M. Li et al., 2022; Mirhajianmoghadam et al., 2021; Read et al., 2014, 2015; Wen et al., 2020; Wu et al., 2018). As stated before, the only publication based on adults reporting LMA is longitudinal (Ulaganathan et al., 2019b). Furthermore, as can be seen below, the three publications with adult data not reporting LMA are the ones with the highest percentage of myopic participants in the sample. LMA might thus be more readily seen in children, but more data is needed to confirm this potential pattern. In children, the investigated ages span 5–18 years, the age range – where reported – varying between one (M. Li et al., 2021) and nine years (Bhandari et al., 2022). As can also be seen in Figure 3.2, there was no apparent pattern regarding participant age and reporting LMA.

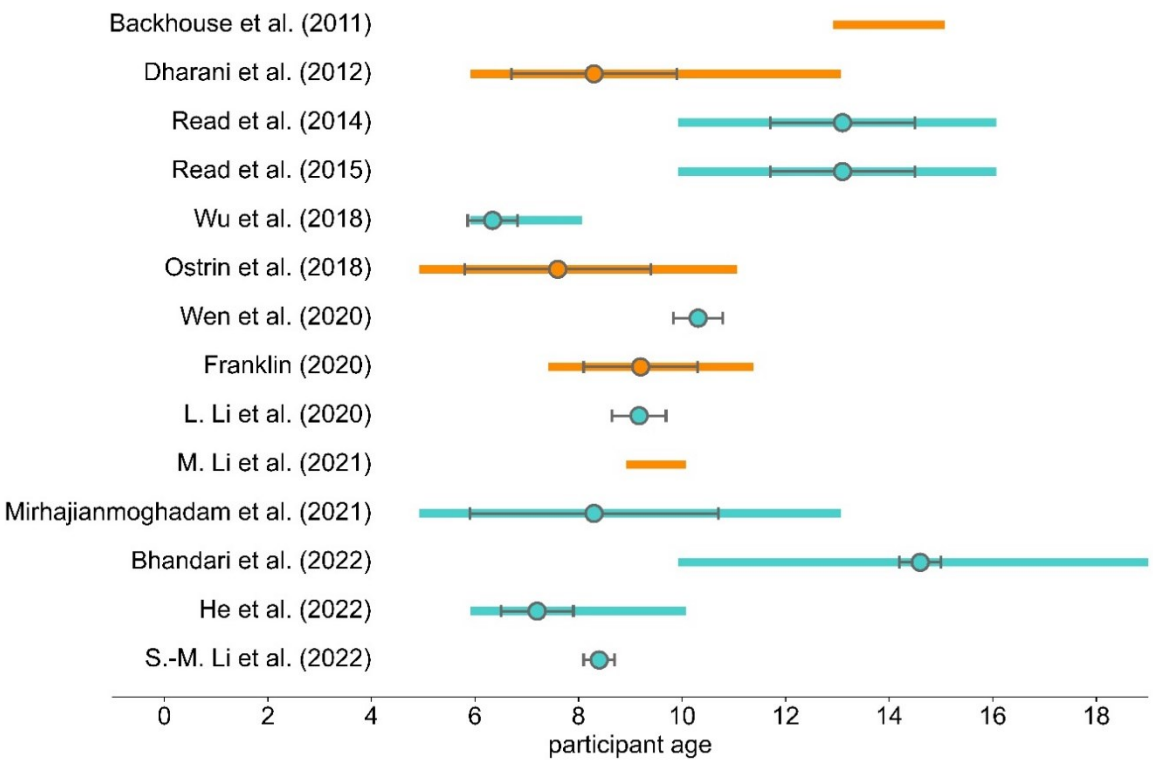


Figure 3.2. Participant age distribution in publications with children. The bars present age range of the sample, the circles and accompanying gray lines indicate mean and standard deviation. Since age range is usually stated in full years in the publications, we presented it as including the year given as the upper limit – e.g., an age range of 13–14 years is presented as 13–14.99 years. Turquoise bars indicate that the publication (strongly) supports LMA, Orange bars indicate no or only minor support for LMA. If available, the information is presented for the analyzed sample – otherwise, it refers to the enrolled sample or the sample completing the trial (prior data exclusion for analysis). As no information on mean and standard deviation was available for the complete sample for Read et al. (2015), said information was taken from Read et al. (2014), with 101 of the 102 underlying participants being analyzed in Read et al. (2015).

3.1.3.2.3.3. General Time Spent in Bright Light Levels

Suggestions have been made that high or low bright light exposure of the entire sample may play a role in the results on LMA (Flanagan et al., 2020; Gordon-Shaag et al., 2021; Read et al., 2014). Thus, we extracted information on the time the overall sample spent in > 1,000 lux, which was most commonly used to estimate time in outdoor light. For four publications, no such data exist (X. He et al., 2022; L. Li et al., 2020; Schmid et al., 2013; Wu et al., 2018). The overall time spent in > 1,000 lux varied largely – from 0.5 hours/day (mean all; Bhandari et al., 2022) to 1.67 hours/day (mean myopes) and 1.98 hours/day (mean emmetropes), respectively (Wen et al., 2020). Eleven publications include data on average lux exposure (mean or median; Alvarez & Wildsoet, 2013; Bhandari et al., 2022; Dharani et al.,

2012; Franklin, 2020; M. Li et al., 2021; S.-M. Li et al., 2022; Mirhajianmoghadam et al., 2021; Ostrin, 2017; Read et al., 2014, 2015; Wen et al., 2020). Here, the values varied between 164 lux (median; Franklin, 2020) and 1,669.46 lux (mean; Ostrin, 2017). There was no apparent relationship between time in > 1,000 lux or average light exposure and results on LMA. Importantly, measured time spent in > 1,000 lux and average light exposure may not only vary due to "real" exposure, but also due to factors like device specifications or wearing position. Yet, findings such as Clouclip having been used in the publications with the least (Bhandari et al., 2022) as well as the most (Wen et al., 2020) > 1,000 lux exposure show that such between-publication differences are not only determined by device specifications or wearing position. What may also potentially complicate comparisons is the fact that the times during which lux data was analyzed vary between publications. This will be discussed further in the data analysis and interpretation section, but regarding the light exposure aspects discussed here, no systematic variation was apparent with regard to analyzed times. Although we did not find a pattern regarding findings on LMA, the large variability in overall exposure time to > 1,000 lux as well as average lux exposure suggest that a sample's general light exposure might indeed be a relevant factor to consider when assessing LMA, and there are many aspects that may complicate respective assessments.

3.1.3.2.3.4. Assessment of Refractive Status and Refractive Error Classifications

There are various ways to assess refractive status and to classify refractive error, and it can be assumed that the choice of method has an impact on the measured refractive status, as well as on which and how many participants will be classified into the respective refractive error groups. For example, non-cycloplegic autorefraction has repeatedly been shown to overestimate myopia compared to cycloplegic autorefraction, especially in younger children (Grzybowski et al., 2020; Rudnicka et al., 2016). Furthermore, cycloplegic autorefraction has been found to be more sensitive in measuring refractive error, and to measure a more myopic spherical equivalent refraction (SER) compared to non-cycloplegic subjective refraction, with the between-method difference decreasing with age (Hashemi et al., 2016).

In 13 publications, participants were classified into refractive error groups, which were then used for analyses on light exposure. Classification was based on history and habitual correction in one publication (Ostrin, 2017), and on a questionnaire indirectly assessing refractive status in two (Bhandari et al., 2022; Mirhajianmoghadam et al., 2021). In the other ten publications, SER was used, whereby Dharani et al. (2012) do not state its kind. Apart from that, either subjective, non-cycloplegic refraction (Read et al., 2014, 2015; Schmid et al., 2013; Ulaganathan et al., 2019b) or cycloplegic autorefraction (X. He et al., 2022; M. Li et al., 2021; Ostrin et al., 2018; Wen et al., 2020; Wu et al., 2018) was measured. In X. He et al. (2022), the analysis regarding light exposure was not performed with the refractive groups per se, but with incident myopia. Schmid et al. (2013) further split myopic participants into stable

and progressing based on their history. In four additional publications, refractive error groups were not used for analyses on LMA, but were defined nonetheless based on autorefraction, either without (Alvarez & Wildsoet, 2013) or with (Franklin, 2020; L. Li et al., 2020; S.-M. Li et al., 2022) cycloplegia. Lastly, Backhouse et al. (2011) did not group participants via refractive status, but report cycloplegic autorefraction measurements. Thus, 15 publications include direct measurement of refraction: In one, the way of measurement is unspecified (Dharani et al., 2012), four report non-cycloplegic subjective refraction (Read et al., 2014, 2015; Schmid et al., 2013; Ulaganathan et al., 2019b), one non-cycloplegic autorefraction (Alvarez & Wildsoet, 2013), and nine cycloplegic autorefraction (Backhouse et al., 2011; Franklin, 2020; X. He et al., 2022; L. Li et al., 2020; M. Li et al., 2021; S.-M. Li et al., 2022; Ostrin et al., 2018; Wen et al., 2020; Wu et al., 2018).

SER cut-offs for myopia, usually either applied on the eyes' average or the right eye, were defined in 14 publications. The most liberal cut-off was < -0.25D SER (Ostrin et al., 2018). The overwhelming majority of publications used the common ≤/< -0.50D SER (Dharani et al., 2012; Franklin, 2020; X. He et al., 2022; L. Li et al., 2020; M. Li et al., 2021; S.-M. Li et al., 2022; Read et al., 2014, 2015; Schmid et al., 2013; Wen et al., 2020; Wu et al., 2018), though as described, this was based on different ways of refraction measurements: Subjective, non-cycloplegic refraction, cycloplegic autorefraction, or a non-specified refraction measurement are reported in the respective publications. Read et al. (2014, 2015) additionally specified at least one eye needing to exhibit < -0.75D SER apart from both eyes' average being ≤ -0.50D, and Franklin's (2020) ≤ -0.50D SER cut-off needed to be fulfilled for either eye. Both reanalyses (Landis et al., 2018; Read, Vincent, et al., 2018) used the ≤ -0.50D SER cut-off, with Landis et al. (2018) also applying the additional criteria as Read et al. (2014, 2015). In two publications, having used either non-cycloplegic subjective refraction (Ulaganathan et al., 2019b) or non-cycloplegic autorefraction (Alvarez & Wildsoet, 2013), more restrictive cut-offs of ≤ -0.75D SER (Ulaganathan et al., 2019b) and ≤ -1.00D SER (Alvarez & Wildsoet, 2013) were applied, respectively. There was no apparent pattern regarding LMA for both refractive status assessment and refractive error classification, but as both display some between-study methodological variability, these aspects should be kept in mind nonetheless.

3.1.3.2.3.5. Percentage of Myopic Participants

The within-sample distribution of refractive status may also be of interest when analyzing potential effects on refractive status. For example, possible differences between myopic and non-myopic participants or myopia-related associations with refractive status might be difficult to detect if there are only few myopic or non-myopic participants. Since amount and type of information on participants' refractive status vary substantially between publications, we present the percentage of myopic participants in the sample to investigate

this aspect. Of course, aspects like range, mean, standard deviation or skewedness of refractive status may also be relevant. Backhouse et al. (2011) do not report a percentage of myopic participants, so we calculated it based on a ≤ -0.50D SER myopia cut-off. A great variance in the proportion of myopic participants between publications is readily apparent, ranging from 4.4% (Franklin, 2020) to 85.2% (Alvarez & Wildsoet, 2013). When only considering publications that specifically analyzed light exposure with regard to refractive groups, the percentage of myopic participants ranges from 13.3% (Ostrin et al., 2018) to 67.3% (Ostrin, 2017).

It is interesting to note that while the publication with the lowest percentage of myopia (4.4%; Franklin, 2020) did not find LMA, the publications with the second and third lowest percentage (6.8% and 10.53%; X. He et al., 2022 and Wu et al., 2018) did. Both were intervention studies with many enrolled participants, namely 6,295 (X. He et al., 2022) and 930 (Wu et al., 2018). The three publications with the highest proportion of myopic participants (62.9%, 67.3% and 85.2%; Schmid et al., 2013, Ostrin, 2017 and Alvarez & Wildsoet, 2013) report no LMA, and their samples are all sized N = 55 or below. This might point to large sample sizes being necessary to assess LMA in case of rather unevenly distributed refractive error or status. However, assuming a pattern based on these few observations is highly speculative, and it should also be noted that the three publications with the highest proportion of myopic participants investigated adults (Alvarez & Wildsoet, 2013; Ostrin, 2017; Schmid et al., 2013), while those with the smallest proportion investigated children (Franklin, 2020; X. He et al., 2022; Wu et al., 2018).

3.1.3.2.4. Data Analysis and Interpretation

3.1.3.2.4.1. IO-Cut-Off

As described above, the chosen IO-cut-off is worth considering, especially since 1,000 lux is commonly applied, but may not always be the best estimator to distinguish indoor from outdoor light. In three publications, an IO-cut-off was either not needed (L. Li et al., 2020; Read et al., 2015), or not based on lux alone (X. He et al., 2022). The 1,000 lux IO-cut-off was chosen in 14 publications (Alvarez & Wildsoet, 2013; Backhouse et al., 2011; Bhandari et al., 2022; Dharani et al., 2012; Franklin, 2020; M. Li et al., 2021; S.-M. Li et al., 2022; Mirhajianmoghadam et al., 2021; Ostrin, 2017; Ostrin et al., 2018; Read et al., 2014; Ulaganathan et al., 2019b; Wen et al., 2020; Wu et al., 2018). Thereby, Alvarez and Wildsoet (2013) had originally determined 882 lux as IO-cut-off based on own measurements, but as the results did not differ compared to 1,000 lux, they used the latter for consistency. Schmid et al. (2013) applied two IO-cut-offs, one potentially including some bright indoor light (500 lux) and one definitely only including outdoor light (10,000 lux). Thus, despite the use of varying devices with different specifications, the 1,000 lux IO-cut-off was applied in almost all publications, including the reanalyses (Landis et al., 2018; Read, Vincent, et al., 2018).

3.1.3.2.4.2. Basis of IO-Cut-Off

We examined the justification of the IO-cut-off within the 15 publications using one. Own pre-measurements for its determination are only reported in three publications, two (Alvarez & Wildsoet, 2013; Schmid et al., 2013) of which used similar devices for these pre-measurements and data acquisition, and one (Wu et al., 2018) used a luxmeter for the pre-measurements. In all other publications, usage of the chosen IO-cut-off is either not justified or other literature is cited for it.

In some publications, other additional measurements with the devices are reported: Correlations between devices and/or between the devices and a luxmeter were sometimes investigated (Bhandari et al., 2022; Franklin, 2020; Ostrin, 2017; Read et al., 2014), or lux values were measured in various indoor and outdoor conditions (Dharani et al., 2012; Ostrin, 2017). Additionally, Ostrin (2017) tested the devices against an UV sensor and Franklin (2020) investigated how the devices' rotational orientation may affect measurements. Lastly, for their reanalyses, Landis et al. (2018) examined the devices' sensitivity at dim illuminations, and Read, Vincent, et al. (2018) determined the comparability between HOBO Temp/Light data logger and Actiwatch 2. In summary, while the IO-cut-off of 1,000 lux is generally accepted and used for various devices and settings, in the vast majority of cases its appropriateness for the given situation is not verified.

3.1.3.2.4.3. Analyzed Times for Light Data

Differences in analyzed times could complicate between-publication comparisons or a consideration of the overall picture. In fact, the publications differ greatly in the times during which light and/or outdoor data is analyzed. Read et al. (2014, 2015) analyzed light data from 6:00h-18:00h, e.g., for the calculation of daily light exposure in Read et al. (2014), but 24 hours/day are considered for aspects like the daily light exposure pattern. Read et al. (2015) state that the mean light exposure during the excluded times was uniformly low. Some publications used 7:00h-19:00h for analysis (Dharani et al., 2012; Franklin, 2020; X. He et al., 2022; M. Li et al., 2021), including one reanalysis (Read, Vincent, et al., 2018). Wen et al. (2020) analyzed light data from 7:00h-20:00h, stating that a vast majority of light exposure lay within this timeframe. Alvarez and Wildsoet (2013) analyzed light data from sunrise to sunset, and Wu et al. (2018) only analyzed device-measured light data during in-school times, as the wearing compliance was considerably lower out of school. Bhandari et al. (2022) considered data from wake to bed time. Comparably, waking hours were considered in the second reanalysis (Landis et al., 2018).

In the remaining publications, times included in the analyses are not explicitly stated (Backhouse et al., 2011; L. Li et al., 2020; S.-M. Li et al., 2022; Mirhajianmoghadam et al., 2021; Ostrin, 2017; Ostrin et al., 2018; Schmid et al., 2013; Ulaganathan et al., 2019b), though

a device wearing or recording time is specified in all but one (Backhouse et al., 2011). In five cases, 24 hours/day wearing or recording is reported (S.-M. Li et al., 2022; Mirhajianmoghadam et al., 2021; Ostrin, 2017; Ostrin et al., 2018; Ulaganathan et al., 2019b). As a wrist-worn device was used in four of these publications, it is likely that this continuous data was also included in the analysis. In one publication, however, the device was pinned on clothing, so it may not have been worn continuously – though the analysis description indicates that data from 24 hours/day was in fact analyzed (S.-M. Li et al., 2022). Furthermore, daily recording time was specified as 7:00h-7:00h on the following day in this publication (S.-M. Li et al., 2022). In the last two publications without explicit mention of analyzed times, the device wearing time is reported as waking hours (Schmid et al., 2013) and throughout the day (L. Li et al., 2020), respectively.

As (most of) daytime is included for analysis in all publications, the between-publication differences in analyzed times are probably not so problematic for comparisons regarding bright/outdoor light exposure – but for aspects like mean light exposure in the overall sample, between-publication comparisons are difficult if varying times are analyzed, and even more so if the analyzed times are not completely clear. Thus, present differences might indeed conceal potentially relevant associations that might be uncovered when considering more than one publication.

3.1.3.2.4.4. Exclusion and Replacement of Light Data

Like analyzed times, exclusion and replacement of data is important to consider, and again we found high between-publication variability. Thus, the procedures of light data exclusion and replacement will be reported in detail. While they are reported in most publications, the type and amount of information provided varies. Information on the respective details stated is presented in Supplementary Table C3. Here, we focus on (1) criteria for exclusion and/or replacement of specific invalid data, (2) criteria for exclusion of complete days and/or data sets, and (3) reported amount of in- and excluded data. The procedures applied in the two included reanalyses (Landis et al., 2018; Read, Vincent, et al., 2018) are considered here was well – though as Read, Vincent, et al. (2018) refer to the publications describing the acquisition of their reanalyzed data for analysis procedures (Dharani et al., 2012; Read et al., 2014, 2015), this reanalysis will only be mentioned in case of additional information.

(1) Data was sometimes excluded as invalid in case of ≥ 15 minutes of complete inactivity and/or darkness during daytime (indicating covered light sensors and/or device removal; Franklin, 2020; Read et al., 2014, 2015; Ulaganathan et al., 2019b) and replaced if certain criteria applied: In Read et al. (2014, 2015) for any diary-documented "off-wrist" times, light levels were estimated as the average of 5 minutes before and after removal if consistent with the diary as indoors or outdoors (1,000 lux IO-cut-off). In Read et al. (2014),

inconsistency only occurred for diary-recorded outdoor activities, in which case the mean outdoor light level over the same time averaged across all other days was used for estimation. Ulaganathan et al. (2019b) estimated light levels for excluded data as the average light level 5 minutes prior device removal, if consistent with the diary-reported activity. If not, the respective data was removed. Franklin (2020) substituted excluded data – on valid days only, see below – with the average for the same time period from valid days. Reanalyzing data from Read et al. (2014, 2015), Landis et al. (2018) describe that the activity diary was used to estimate illuminance for non-wear times.

(2) Often, criteria were defined for excluding days and/or data sets. Dharani et al. (2012) excluded days with all light measures < 100 lux, assuming non-wear of the device. Read et al. (2014, 2015) only included days with ≥ 90% of valid data to determine average daily minutes in > 1,000 lux. Ostrin (2017) and Ostrin et al. (2018) excluded days with device removal for > 30 minutes or zero light exposure for ≥ 30 minutes during daylight, and nights if the device had been removed for any part of it. Wen et al. (2020) only considered days with data from ≥ 80% of the required wearing time and data sets encompassing at least three weekdays and one weekend day (one week measurement period) as valid. Franklin (2020) only included days including 90% of valid data during daytime and data sets with at least five (out of nine) valid days. Data was excluded in M. Li et al. (2021) if at least one weekday and one weekend day of device wear was missing from the 14-day measurement period, or if wear days had an average light intensity of ≤ 100 lux or entries of 0 lux for ≥ 60%. Bhandari et al. (2022) considered days with ≥ 8 hours of data during wake time as valid, and required at least 3 valid weekdays and 1 valid weekend day (one week measurement period) for including the participant. S.-M. Li et al. (2022) did not include measurements with fixed illumination values, assuming non-wear of the device. Finally, in their reanalyses, Landis et al. (2018) eliminated days with device removal of > 90%, and Read, Vincent, et al. (2018) only included weekend data from children who had participated during school vacation in Dharani et al. (2012) for comparability. As can be seen, there is substantial between-publication variability regarding exclusion practices.

(3) Information on the amount of in- and excluded data is given in most of the publications reporting respective procedures, and is presented in Table 3.2.

Table 3.2

Amount of Data In- and Excluded via the Publications' Exclusion Criteria Described in (2)

publication	data sets[a] excluded	days included for analyzed data sets (*M*±*SD*)	additional information
		42 days	
Ostrin et al. (2018)	n/a	13.9±2.9 (per 14-day session)	3x14-day measurement; 18 days excluded over all sessions (< 1%)
		28 days	
Read et al. (2015)	n/a	26.2±3.1 (overall) 13.4±1.5 (session 1) 13.1±1.7 (session 2)	2x14-day measurement
Read, Vincent, et al. (2018)	n/a	25.4±3.3	2x14-day measurement; reanalysis of prior data (Read et al., 2014, 2015)
Landis et al. (2018)	n/a	23.5±0.34	2x14-day measurement; reanalysis of prior data (Read et al., 2014, 2015)
Ulaganathan et al. (2019b)	0 (winter) 6 (16.2%; summer)	13.5±2.0 (winter) 13.3±1.8 (summer)	2x14-day measurement
		14 days	
Read et al. (2014)	1 (1%)	13.4±1.5	no exclusion procedure for data sets specified, but 1 participant excluded due to only 7 h of valid data overall; 6±11% of total data invalid, ca. 2% of analyzed data estimated (see (1))
Ostrin (2017)	n/a	13.2±1.4 (days) 14.2±1.3 (nights)	
Wu et al. (2018)	n/a	n/a	2x7-day measurement; 96% wearing compliance during in-school times at study end
M. Li et al. (2021)	93 (16.1%)	n/a	

Table 3.2 – Continued

Amount of Data In- and Excluded via the Publications' Exclusion Criteria Described in (2)

10 days			
Mirhajianmoghadam et al. (2021)	n/a	7±1 weekdays 2.4±0.7 weekend days	no exclusion procedures specified
9 days			
Franklin (2020)	54 (36.2%; after exclusion of 39.7% days)	not reported	some participants wore the device multiple times; 1.1% of the analyzed data substituted (see (1))
7 days			
Read, Vincent, et al. (2018)	n/a	6.6±0.7	reanalysis of prior data (Dharani et al., 2012)
Wen et al. (2020)	not reported	3.98±0.36 weekdays 1.13±0.11 weekend days	
Bhandari et al. (2022)	18 (34.0%)	6.6±0.7	

Note. A cell is marked n/a if the associated exclusion procedure is not described as having been done in the respective publication. [a]A data set describes data from one measurement session – in some cases, there are more data sets than participants due to multiple measurement sessions per participant.

While for most publications, the mean days included in analysis – after potential exclusion of complete data sets – are at maximum 1 day fewer than the measurement period, there is some between-publication variation in the amount and proportion of included days. With regard to the exclusion of complete data sets, a varying percentage was excluded in the publications. Apart from aspects like participant age, devices or circumstances of data acquisition which may influence compliance and data quality, the varying in- and exclusion procedures are a potential factor underlying these differences. For example, in the publications where a criterion to exclude complete data sets had been applied, the percentage of excluded data sets is generally rather high (16.1–36.4%), while no such procedure had been applied in many other publications – in most of which it was indeed apparent from the data that no complete data sets were excluded. In general, given the various applied data in- and exclusion procedures, the apparent variation between publications with regard to the amount of excluded data is not surprising, though comparisons are inherently difficult due to the various approaches.

3.1.4. Discussion

We identified ten wearable light meters from studies on light exposure and myopia in humans, and included 20 publications in our analysis of research methods, two of which were reanalyses. The devices show large differences, for example in how they are worn, or their lux measurement range and spectral sensitivity. In the following, aspects related to the devices, as well as publications and research methods will be discussed and put into context. For the considerations mainly related to light meter characteristics, the devices will be grouped based on how they are usually worn. We will conclude by presenting a list of aspects that, in our opinion, should be considered when investigating LMA.

3.1.4.1. Light Meter Characteristics – Devices Attached Over Clothing

The HOBO Temp/Light data logger is generally worn over clothing, e.g., attached with a pin, and was used in the earliest publications. Its spectral sensitivity strongly deviates from the photopic luminous efficiency function, with the manufacturer stating that the light sensor measures a much wider wavelength spectrum than is humanly visible (Onset Computer Corporation, 2012). Importantly, most other devices' light sensors also do not exactly fit the photopic luminous efficiency function, albeit they seem to deviate less strongly. Wearing the HOBO Temp/Light data logger may be more laborious compared to other light meters, and as it is usually worn forward-facing on clothing, it may easily be covered, e.g., with a jacket. Also, the device can probably be worn during fewer activities than some other devices. For example, it is impractical to wear at night – though this is presumably not a large problem when investigating bright light – and even though it is waterproof, showering or swimming with it would be difficult due to its usual ways of wearing. Comparable considerations also apply to MyLyt, which, however, was not used in any of the publications included in the analysis of research methods. Aspects like these might have played a role in the four earliest publications not finding LMA – though the two most recent publications with the HOBO Temp/Light data logger did find LMA, both including a large number of participants (S.-M. Li et al., 2022; Wu et al., 2018). Furthermore, in both publications, teachers (Wu et al., 2018) or teachers and parents (S.-M. Li et al., 2022) were instructed to monitor device wear, and Wu et al. (2018) only analyzed in-school times regarding objective light exposure. In general, there are some challenges regarding the wearability of devices attached over clothing, and for the HOBO Pendant Temp/Light data logger, one may also want to consider the spectral sensitivity function strongly deviating from the photopic luminous efficiency function.

3.1.4.2. Light Meter Characteristics – Devices Worn on Spectacles

Clouclip and Vivior Monitor are spectacle-worn and thus measure eye-level light intensity – on the other hand, their way of wearing as well as the fact that neither one is waterproof restrict potential activities. No publication with Vivior Monitor is included in the analysis of research methods, but interestingly, all three publications based on Clouclip data report LMA (Bhandari et al., 2022; L. Li et al., 2020; Wen et al., 2020). Measuring of eye-level light intensity may thereby play a role, as light entering the eye is probably more relevant for myopia (development) than general ambient illumination. Another potential limitation of spectacle-worn devices is that myopic and non-myopic participants are subject to different alterations during data acquisition, since the former mostly do and the latter do not wear spectacles in real life. Indeed, in a study with 5th-graders wearing Clouclip, myopic participants reached the required wearing time more often than emmetropic participants (Wen et al., 2019). The authors discuss optimizing the device's wearability, e.g., by constructing it as an earphone (Wen et al., 2019). Something comparable has, for example, been implemented in the Daysimeter, a device designed to measure circadian light exposures: The photosensors of the Daysimeter-S are positioned at the plane of the cornea, but no spectacles are necessary for wearing (Figueiro et al., 2013). Overall, the possibility of measuring eye-level light intensity provided by spectacle-worn devices may be especially relevant when investigating LMA, while other aspects of these devices pose important challenges for field research.

3.1.4.3. Light Meter Characteristics – Devices Worn at Wrist

Wrist-worn devices, if waterproof, can be worn at almost all times. We identified six wrist-worn devices, five of them labelled waterproof per IPX7 (the Actiwatches) or IP68 (Sony Smartwatch 3 used for FitSight). Yet, Franklin (2020) found the Actiwatch 2 seals prone to leaking in 40 °C water and thereafter advised participants not to shower, bath, or swim with the device, remarking that the water resistance recommendation is based on a cold water test (Franklin, 2020). Wrist-worn devices may be covered by clothing, and how problematic this might be likely depends on circumstances like the weather. Light exposure at wrist has been shown to substantially deviate from that at eye-level – more strongly than light exposure measured at chest or at the collar (Aarts et al., 2017; Figueiro et al., 2013). Thus, wrist-worn devices do not seem to measure eye-level light intensity, while measurements near the chest appear to match the latter more closely (Hartmeyer et al., 2022). Systematic variations have even been found, e.g., wrist measurements tending to overestimate eye-level light exposure in indoor conditions and to underestimate it in outdoor conditions (Hartmeyer et al., 2022). All these aspects may influence light measurements, and confound comparisons between measurements with devices worn at different body locations. Thus, while the easy

wearability and (in most cases) water resistance of wrist-worn devices post clear advantages for field studies, aspects like accidentally covering them or their measurements deviating from that of devices positioned closer to the eyes are potential challenges when measuring light exposure.

3.1.4.4. Time of Publication

The earliest publication included in the analysis of research methods stems from 2011 (Backhouse et al., 2011), so this field of research is relatively young. Noticeably, the four oldest included publications do not support LMA (Alvarez & Wildsoet, 2013; Backhouse et al., 2011; Dharani et al., 2012; Schmid et al., 2013). One may speculate whether aspects such as the lack of established procedures or experience regarding compliance enhancement or exclusion of data play a role. For example, as compared to most other publications, no or only few data pre-processing was conducted. However, said publications also share other criteria like the light meter, and no conclusion regarding LMA can be drawn based on time of publication alone.

3.1.4.5. Type of Study

The finding of longitudinal, but not cross-sectional, studies using light meters reporting associations between higher light exposure and slower eye growth (Lingham et al., 2020) is not reflected in our analysis, as results supporting LMA have been reported in both types of investigations. The fact that LMA have been found cross-sectionally may suggest that a person's bright light exposure is somewhat stable over time – and may have played a role in whether or not myopia had developed earlier in their life. On the other hand, these cross-sectional results could also be explained by myopic participants being more likely to spend time indoors than emmetropic participants.

3.1.4.6. Sampling Interval and Measurement Duration

A sampling interval of ≤ 2 minutes (Alvarez & Wildsoet, 2013; Ulaganathan et al., 2017) and a measurement duration of ≥ one week (Ulaganathan et al., 2017) have been proposed to ensure reliable (outdoor) light measurements. These settings should be considered when planning measurements, as, e.g., Ulaganathan et al. (2017) note that differences in these aspects may be one factor underlying between-study differences in findings regarding personal ambient light exposure – though since the recommendations are fulfilled in most

publications included here, it is unsurprising that no pattern regarding results on LMA was apparent.

3.1.4.7. Geographic Location

Data on objectively measured light exposure with regard to myopia is missing for most parts of the world as the publications originate from only six countries. Interestingly, some LMA in school-aged children were discovered in all five East Asian (X. He et al., 2022; L. Li et al., 2020; S.-M. Li et al., 2022; Wen et al., 2020; Wu et al., 2018), but not (Dharani et al., 2012) or only minimally (M. Li et al., 2021) in both Singaporean publications, despite the high myopia prevalence in school children in both regions (Ding et al., 2017). Here, one may consider the overall time spent in bright light. For example, Read et al. (2014) speculate that Dharani et al. (2012) may not have found a difference in time outdoors between myopic and emmetropic participants because some of the latter were already on their way to becoming myopic due to low overall light exposure. They also note the consistency of this with the high myopia prevalence in Singapore (Read et al., 2014). In the Singaporean publications (Dharani et al., 2012; M. Li et al., 2021), overall mean light levels and time in ≥ 1,000 lux were reduced compared to the one East Asian publication with this information available (for more than in-school times; Wen et al., 2020). As participants in the latter were on average older than in the Singaporean publications, one would rather expect a reverse pattern. Even though this is speculative and based on few data, it is worth to keep an eye on. Also, data from other parts of the world is needed for a more comprehensive picture of LMA.

3.1.4.8. Season

Due to the relationship between myopia development and season (Cui et al., 2013; Donovan et al., 2012; Gwiazda et al., 2014), the latter may potentially influence the measurement of LMA. Yet, seasons were not only very diverse between publications – data acquisition was also often not controlled in this respect, and only three publications investigated season with regard to LMA, yielding mixed results. It would be advisable to control and investigate season more thoroughly in research on LMA, a first step being to always specify the time and season of data acquisition. Also, one should control season with regard to participant groups, for example by matching participants from different groups to simultaneously wear the light meter as Read et al. (2014) did. Importantly, season and geographic location are of course intertwined.

3.1.4.9. Participant Sample Size and Characteristics

There is large between-publication variability in sample size and participant age. Publications with a larger sample tended to support LMA more often than others. Age-wise, there were only four publications on adults and 14 on children – with one and nine of them supporting LMA, respectively. Due to the low number of publications with adult data, comparing adult and child publications regarding the proportion of publications (not) reporting LMA is not that informative. As axial myopia usually appears during childhood and youth (Morgan & Rose, 2005), it does make sense that the focus lies primarily on these ages. Furthermore, with the large age (range) variance between publications with children, it is not surprising that no pattern emerged regarding age and results on LMA. However, age should be investigated further with respect to potential protective effects of light exposure: Since myopia development does not happen in the same way across all of childhood (Morgan & Rose, 2005), more knowledge on relevant ages for the influence of light exposure may improve the development of preventive measures. With respect to sample characteristics, homogeneity regarding relevant behaviors may also be of interest. For example, Burfield et al. (2019) speculate that due to similar schedules, their sample of emmetropic and myopic young adult university members may have been too homogeneous in light exposure and sleep- wake patterns to uncover associations – in this case, primarily regarding light exposure and diurnal rhythms. Of the four included publications investigating adults, three had a university student sample (Alvarez & Wildsoet, 2013; Schmid et al., 2013; Ulaganathan et al., 2019b) and one had a sample with unspecified occupations – but with a mean age of 37 years (range: 21–64), participants were probably not (exclusively) students (Ostrin, 2017). While this point is indeed interesting, four publications are not sufficient to analyze whether such homogeneity in adult participants may play a role in the results. However, it should be kept in mind, especially since lack of diversity in samples can be a large problem for analyzing, interpreting and generalizing results, as is well known in psychological research (Henrich et al., 2010). In any case, while there is no clear picture as of yet, potential associations between participant age and LMA may become clearer with more data in the future, and aspects such as sample homogeneity in relevant characteristics should be considered.

3.1.4.10. General Time Spent in Bright Light Levels

The overall time participants in a sample spent in bright light has been suggested to affect LMA by concealing them due to an overall low exposure (Flanagan et al., 2020; Read et al., 2014), or by the protective effect of light exposure on myopia reaching a ceiling effect in case of overall high exposure (Gordon-Shaag et al., 2021). We discovered large between-publication variability in "outdoor light" (> 1,000 lux) and average light levels. Importantly, it is difficult to determine how much of this is based on variability in actual light exposure versus

on measurement differences, e.g., due to device specifications or ways of wearing – though findings such as Clouclip having been used in both the publication with the least (Bhandari et al., 2022) and the most reported > 1,000 lux exposure (Wen et al., 2020) suggest that the device is not the only factor responsible for such variability. More research is warranted to detangle these aspects – also including between-publication differences in analyzed times and whether different devices are comparable regarding the measurement of time in > 1,000 lux – and assess the implications of a population's overall (bright) light exposure.

3.1.4.11. Assessment of Refractive Status as Well as Classification and Proportion of Myopic Participants

Some between-publication variability was also discovered regarding the assessment of refractive status, and the classification and proportion of myopic participants. While in most publications, direct measures of refraction were used to assess refractive status, some applied indirect measures. For an SER-based myopia classification, the common -0.50D SER cut-off was mostly used, and the underlying refractive status measurements were either non-cycloplegic subjective refraction, cycloplegic autorefraction or, in one case, unspecified. The percentage of myopic participants ranges from 4.4% (Franklin, 2020) to 85.2% (Alvarez & Wildsoet, 2013) between publications. Notably, of the three publications with the lowest (Franklin, 2020; X. He et al., 2022; Wu et al., 2018) and highest proportion of myopic participants (Alvarez & Wildsoet, 2013; Ostrin, 2017; Schmid et al., 2013), only those with a very large sample size strongly support LMA (X. He et al., 2022; Wu et al., 2018). However, whether this observation is meaningful cannot be determined with the few included publications. In any case, it is important to consider that measurement, definition and distribution of participant characteristics may influence analyses and results.

3.1.4.12. IO-Cut-Off

One extremely relevant aspect when assessing light and outdoor exposure is the IO-cut-off. In all but one (Schmid et al., 2013) of the 15 publications using an IO-cut-off, it was set at 1,000 lux. Own pre-measurements to determine said IO-cut-off were only mentioned in three publications (Alvarez & Wildsoet, 2013; Schmid et al., 2013; Wu et al., 2018). And although 1,000 lux is widely accepted as IO-cut-off even beyond this specific research field, it is indeed questionable if it is always appropriate for the given circumstances. In fact, other IO-cut-offs have been applied before, e.g., 800 lux with Clouclip (Wen et al., 2017) or 200 lux with the Actiwatch Spectrum (Refinetti, 2019). Two aspects in particular are important, namely (1) whether 1,000 lux is an accurate cut-off to distinguish indoors from outdoors, and (2) how comparable measurements of 1,000 lux are between different light meters.

Regarding (1), one study, e.g., reported measurements of > 1,000 lux not only outdoors, but also indoors near a window even with a calibrated photometer (Howell et al., 2021). Although perfectly distinguishing indoors from outdoors via any one solely lux-based IO-cut-off is most likely impossible, such findings do call into question whether 1,000 lux is in fact the ideal IO-cut-off in any given situation to classify environments as accurately as possible. For example, as lighting conditions are darker in winter than in summer, different IO-cut-offs may be useful in different seasons – with the same IO-cut-off, time outdoors may be overestimated in summer and underestimated in winter. Regarding (2), it has, e.g., been found that despite a generally high correlation between lux measurements of Clouclip, Actiwatch 2 and a photometer, the lux values corresponding to 1,000 lux as measured with the photometer were 533.15 lux for Actiwatch 2 and 850 lux for Clouclip (Howell et al., 2021). Importantly, these values represent the devices' lux measurement best matching the photometer-measured 1,000 lux and not their best IO-cut-off – but the finding does underline the notion that different devices' lux measurements cannot necessarily be compared to one another. This is also represented in the fact that the Actiwatch 2 underestimates lux compared to a photometer, while the opposite is true for the Actiwatch Spectrum (Figueiro et al., 2013; Howell et al., 2021; Markvart et al., 2015). Furthermore, our own research (Hönekopp & Weigelt, unpublished data[5]) suggests that even when worn at exactly the same time, some light meters are better at correctly recognizing indoor than outdoor time and vice versa with the 1,000 lux IO-cut-off. Furthermore, other IO-cut-offs, which varied between devices, were more accurate. These findings also suggest that (1) 1,000 lux is not always an accurate IO-cut-off and (2) 1,000 lux measurements are not necessarily comparable between devices. 1,000 lux not always accurately separating indoor and outdoor locations may partly explain the often poor correlation between objective and subjective outdoor time estimations (Mahroo et al., 2013). In fact, other IO-cut-offs have sometimes been found to better correspond to subjective measures (Dharani et al., 2013; Wen et al., 2021). What needs consideration here is if one actually aims to assess time spent outdoors vs indoors with this IO-cut-off, or if one rather wants to investigate time spent in brighter vs less bright light intensities, roughly resembling "outdoor-like" and "indoor-like" light levels, not being particularly interested in the environment participants were actually in. The former may, e.g., be the case if one is (also) interested in influences other than higher light intensity that outdoor environments may have on myopia development (Howell et al., 2021). For example, different chromatic spectra of indoor and outdoor light may play a role, as the spectral composition of light has been found relevant with regard to emmetropization, ocular growth and myopia development in animal models (French et al., 2013; Muralidharan et al., 2021).

[5] The data in question is presented in Study 5 (footnote not included in the published paper).

In the latter case, i.e., if one primarily wishes to distinguish time spent in brighter vs less bright light intensities, (1) is less relevant – but it would still be problematic to compare data from different devices if 1,000 lux measurements were not comparable between them as described in (2). If one actually wants to best distinguish indoors from outdoors, one could consider including other measurements. For example, Vivior Monitor can additionally measure UV exposure, which could be used instead of or together with lux data. The latter is described for the Akeso eye care glasses (Fan et al., 2022), and Ye et al. (2019) used lux, UV and step data measured by Mumu in their model for indoor-outdoor discrimination. Generally, more methodological assessments are needed with regard to implications of the IO-cut-off, and it is advisable to consider and test which IO-cut-off is best for an investigation's circumstances.

3.1.4.13. Analyzed Times for as Well as Exclusion and Replacement of Light Data

We detected large variability between publications regarding analyzed times of light exposure and other data exclusion and replacement procedures – this is especially relevant for comparing results of different publications. Usefulness and feasibility of potential procedures thereby depend on various factors like when the device can be worn, circumstances of data acquisition, or outcome measures. Thus, while unification of procedures would certainly be beneficial in some regards, it would presumably be difficult to achieve. Yet, it is important to at least thoroughly report procedures as well as rates of data exclusion and replacement, and to consider them when assessing or planning investigations. For the sake of comparability and consideration of the overall picture, it might also be useful to always report certain values (e.g., mean lux during waking hours or between sunrise and sunset), which can then be compared between publications, even if the specific study focuses on other values.

3.1.4.14. Selected Relevant Aspects in the Study of Light-Myopia Associations

We will conclude with a list of aspects which we believe are relevant to the study of LMA with wearable light meters. Importantly, this list should not be considered exhaustive.

- Choose the light meter to suit the circumstances of data acquisition (e.g., regarding battery life, water resistance, body position, wearability), thereby also considering whether any device specifications – or not knowing them – are problematic.
- Report the geographic location of data acquisition for comparability reasons. Furthermore, it would be desirable if investigations on LMA were conducted in more parts of the world than they are now.

- Likewise, report the season of data acquisition, and ideally consider it in study design and analysis because of its potential influence on LMA.
- Thoroughly report potentially relevant details of the participant sample, especially those that the international community might not be aware of (e.g., school entry age), and keep in mind that sample homogeneity in relevant aspects might be problematic.
- Thoroughly report the assessment of refractive status as well as the classification of refractive error groups.
- Choose the IO-cut-off based on the circumstances of data acquisition (e.g., device, weather) and what is to be achieved with it (e.g., actual outdoor- and indoor-time vs "indoor-like" and "outdoor-like" lighting environments, comparison with other investigations). Ideally, conduct pre-measurements for its determination and explain your choice(s).
- Consider which times to include in the analyses of light data, and which pre-processing procedures to apply (e.g., any data exclusion and/or replacement), and thoroughly report the procedures.
- In this context, also report the amount of excluded and replaced data.

3.1.5. Limitations

Naturally, this review is subject to limitations as we were not able to cover all interesting aspects with regard to the investigation of LMA – for example, the differentiation between autorefractor measurement methods (for the models used in each publication, see Supplementary Table C3), other visual assessments than that of refractive status and/or myopia classification, statistical procedures to assess LMA or to pre-process data like logarithmic transformation (Hartmeyer et al., 2022), or the variability in measurements of the same light meter type (for device calibration and additional lux measurements reported in each publication, see Supplementary Table C3; Markvart et al., 2015).

As per the dedicated focus of the review, we only investigated publications regarding white light exposure (lux). Aspects like the spectral composition of light were not considered, but – as pointed out earlier – are in fact very interesting regarding the protective effect of time outdoors on myopia (French et al., 2013; Muralidharan et al., 2021), and some light meters can and have been used to measure the spectral composition of light (Abbott et al., 2018; Harb et al., 2016).

3.1.6. Conclusion

Various light meters have been used to assess the relationship between myopia and light/outdoor exposure. These differ in various technical specifications – not all of which are publicly available – and in aspects like wearability or how they are worn. We reviewed the literature on LMA with regard to general characteristics, data acquisition, participant population, as well as data analysis and interpretation of the publications, discussing several aspects that warrant critical consideration, for example the common use of the 1,000 lux IO-cut-off. We found very high between-publication variability for many methodological aspects, and extremely limited for others. This makes it conceivable that some of these methodological aspects may contribute to between-publication variety in the results. The between-publication variability in methodological aspects often being very high or barely present may also impede the ability to find patterns between these aspects and results on the association between myopia and light exposure. The considered aspects were usually described thoroughly within the publications. Sometimes, information was missing, which would have been important to comprehensively assess and compare the respective publications. Missing information also occurred with regard to relevant light meter specifications like their spectral sensitivity, and in some cases, it was not possible for us to obtain them even after contacting manufacturers and/or authors.

In general, we demonstrate the wide variability between devices used for research on myopia and light exposure and discuss the implications thereof. We additionally identify and discuss relevant methodological aspects of the publications, highlighting areas where more research is needed and outlining factors that should be considered when planning similar investigations.

3.1.7. Acknowledgements

We acknowledge financial support by Deutsche Forschungsgemeinschaft and Technische Universität Dortmund/TU Dortmund Technical University within the funding program Open Access Publishing.

3.1.8. Disclosure of Interest

The authors report no conflicts of interest in this work.

3.2. Study 5:

Comparing Simultaneously Worn Light Meters: Light Exposure Measurements, Indoor-Outdoor Distinctions and Implications for Myopia Research

Abstract: Research on the association between objective light exposure and myopia uses various light meters, which raises the question of comparability. Thus, we compared measurements of different, simultaneously worn light meters, namely HOBO Pendant UA-002-64, Actiwatch 2, Actiwatch Spectrum PRO, Clouclip M2, and Vivior Monitor. One experimenter simultaneously wore five light meters that have previously been used in research on light exposure and myopia for 12 hours, thereby positioning the light meters as they had been in prior investigations. We assessed the comparability of lux values as well as sensitivity and specificity of the common 1,000 lux indoor-outdoor cut-off and of each light meter's best cut-off determined via ROC curve analyses. Furthermore, as some light meters were worn on two days, we calculated sensitivity and specificity of the other day's best indoor-outdoor cut-off. The light meters measured a similar light exposure pattern, but varied substantially in their absolute values. All light meters exceeded 1,000 lux substantially more often outdoors than indoors, but times and frequencies of correct classification by this cut-off varied between them, as did the associated sensitivities and specificities. Most of the determined best cut-offs were substantially different from the 1,000 lux cut-off and their sensitivities and specificities outperformed those of the latter. The same was true for the other day's determined best cut-offs in almost all cases. Thus, one cannot assume between-device comparability in lux measures or the 1,000 lux cut-off. Furthermore, an individually calculated indoor-outdoor cut-off determined in similar weather and lighting as during the actual data acquisition might improve classification. Therefore, when comparing results on light exposure and myopia or translating them into practice, one should consider the light meters and practices with which they were obtained.

This study is joint work with Sarah Weigelt.

3.2.1. Introduction

The rising prevalence of myopia worldwide is concerning (Holden et al., 2016), which makes examining its pathogenesis all the more important. Increasing evidence from investigations with wearable light meters indicates that light exposure may be an adjustable environmental factor of myopia development: Bright light as well as outdoor light exposure have repeatedly been associated with reduced myopia, sometimes even reduced myopia progression (X. He et al., 2022; Mirhajianmoghadam et al., 2021; Read et al., 2014, 2015; Wu et al., 2018). Not all investigations detect these associations (Dharani et al., 2012; M. Li et al., 2021), however, and more research is also needed regarding the aspects that determine if and to what extent bright (outdoor) light exposure is protective against myopia.

It is therefore important to compare investigations with varying characteristics regarding times spent in different light intensities or indoors versus outdoors (most commonly distinguished via a 1,000 lux cut-off; Dharani et al., 2012; M. Li et al., 2021; Mirhajianmoghadam et al., 2021; Read et al., 2014) and potential associations with refractive status. These investigations often differ in the light meters used. Thus, the question arises how comparable measured light intensities are between different wearable light meters.

Two device-related potential sources of variance in light measurements are the *light meters* themselves and their *position on the body*. Between devices, measurements may differ due to different technical specifications such as spectral sensitivities. Their position on the body may affect measurements because the sensors are oriented differently at different wearing locations. There already is some research on both these factors individually, as well as when wearing *different light meters at different body positions*.

Regarding the *light meters* themselves, it has repeatedly been shown that lux measurements with different light meters deviate from those with a calibrated photometer – with the deviation being linear for individual light meters, but the absolute deviations varying between them (Figueiro et al., 2013; Howell et al., 2021; Joyce et al., 2020). Deviations in measurements between different light meters worn at the same body position have also been found before. For example, comparing measurements of two light meters (Actiwatch Spectrum and Daysimeter) simultaneously worn at wrist revealed significant between-device differences in hourly geometric mean lux levels for most of the daytime (Figueiro et al., 2013). The respective figure (Figure 7; Figueiro et al., 2013) shows that the differences were rather large (often > 100 lux) in relation to the range of hourly geometric mean lux levels (all < 400 lux for Actiwatch Spectrum & < 200 lux for Daysimeter; Figueiro et al., 2013).

With respect to the devices' *position on the body*, several studies report differences between lux measurements of similar light meters worn simultaneously at different positions. For example, Figueiro et al. (2013) found significant differences between lux

measurements of Daysimeters located near the eye and at wrist, but not between a device near the eye and devices worn as a pin on the torso or a pendant around the neck. Using four identical light sensors, Aarts et al. (2017) report illuminance measurement inaccuracies of 11-27% for measurements at wrist, 6-17% for measurements at chest, and 6-8% for measurements on the side of glasses compared to measurements between the eyes. Furthermore, Wen et al. (2021) discuss that lux measurement variations between similar light sensors placed on different parts of the body increase with ambient illuminance. When measuring 23,000 lux in a skyward orientation, they measured 15,000 lux at the line of sight with a slightly upward face, 4,600 lux at chest and 2,300 lux at wrist (Wen et al., 2021).

Thus, it is not surprising that there can be deviations in measurements by *different light meters at different body locations*, though some evidence also suggests that the differences may not be that pronounced: Jardim et al. (2011) compared measurements at wrist (Actiwatch-L) and eye-level (Daysimeter) in hospitalized, post-operative patients. In light levels < 5,000 lux, the mean between-device difference was < 10 lux, with an increased difference in higher light levels. Importantly, the general lighting was rather dim with an average light level of 156 (246) lux measured at eye-level and 128 (116) lux measured at wrist for ICU (cardiac ward) participants, and only 0.3% of eye-level measurements exceeded 5,000 lux (Jardim et al., 2011). Generally, data from this setting may not be generalizable to normal, real-life conditions (Hartmeyer et al., 2022). Aiming to compare the results of two investigations on light exposure and myopia conducted with two different devices (HOBO Pendant UA-002-64 and Actiwatch 2), Read, Vincent, et al. (2018) asked ten adults to simultaneously wear both devices for 60 minutes. While their data was highly correlated ($r = 0.79$ for mean light exposure, $r = 0.95$ for minutes of outdoor exposure at > 1,000 lux) and the between-device difference regarding minutes of outdoor exposure was only M±SD = 0.4±1.1 minutes, there was a significant difference of 4,677±11,048 lux for mean light exposure, again with the largest differences at high light levels. Mean light levels were overestimated with the HOBO Pendant UA-002-64 as compared to the Actiwatch 2 (Read, Vincent, et al., 2018). Van Duijnhoven et al. (2017) had participants simultaneously wear multiple light meters for 4-8 hours. While comparing between-device light measurements was not a focus of the investigation, large deviations in the measurements of six devices can be seen in the figures with exemplary data, with, for example, differences of multiple hundred lux at times – even when all devices measured < 1,000 lux (van Duijnhoven et al., 2017). Comparing measurements over multiple days, Bhandari et al. (2021) found systematically lower illuminance measures by Actiwatch Spectrum Plus than Clouclip, with significant differences in measured outdoor times (minutes in ≥ 1,000 lux) and daily light exposure. In summary, differences between devices worn at different body positions have been found on several occasions, but few studies have specifically focused on systematically measuring and examining this over a longer period of time.

Keeping all this in mind, the comparability of the common 1,000 lux indoor-outdoor cut-off between different light meters is questionable, even in similar conditions. In some cases, different cut-offs were in fact used or discussed. For example, Dharani et al. (2012) used the 1,000 lux cut-off in their investigation on diary- and light meter-measured time outdoors and light levels in Singaporean children. Yet, it was later pointed out that a higher cut-off may have been reasonable instead (Mahroo et al., 2013), and Dharani et al. (2013) agree, stating that 1,500 lux would be the best cut-off for evaluating indoor versus outdoor activities. Howell et al. (2021) empirically derived 533.15 lux and 850 lux as corresponding to photometer-measured 1,000 lux for Actiwatch 2 and Clouclip M2, respectively. In general, findings such as these underline that 1,000 lux is not necessarily the best indoor-outdoor cut-off in all situations.

Here, we measured light exposure (lux)[6] with several, simultaneously worn light meters that have been used in research on light exposure and myopia. Importantly, this is a pilot study involving one subject and one device per type to obtain a sense of the magnitude of between-device variability in lux measurements and the precision of indoor-outdoor discrimination based on lux cut-offs, as both factors are important for interpreting and comparing results on the light-myopia association. Through an activity log accurately kept by the experimenter while wearing the light meters, we were able to thoroughly examine their indoor-outdoor discrimination ability. Prior investigations have shown differences in light intensity measurements between various light meters and body locations, usually comparing a small number of devices, or measuring for only a short period of time, or not specifically analyzing the data in this respect. In this study, we assessed light measurements with five different light meters and six wearing locations from prior investigations on light exposure and myopia in an exemplary real-life field setting from morning to evening (12 hours).

3.2.2. Methods

Five different light meters were included in the study. We identified the light meters and ways in which they have been worn in previous studies by conducting a literature search for human studies on myopia and light exposure (lux), measured with wearable devices. We could not include all identified light meters or ways of wearing. For example, we excluded devices that were not commercially available as well as ways of wearing that were not clear

[6] As generally done in research on myopia and light exposure, we focused on the measurement of illuminance (lux), which – if not otherwise specified – is defined as irradiance weighed by the photopic luminous efficiency function V(λ) (Figueiro et al., 2013; Ohno et al., 2020). Yet, it should be kept in mind that the devices' illuminance estimation is not always accurate, as their spectral sensitivities may for example deviate from V(λ) (Figueiro et al., 2013; Joyce et al., 2020).

to us from the report. Devices that were only used in studies that were published after our literature search were also not included. Table 3.3 presents an overview of the included devices, their technical specifications, the chosen body positions and logging intervals, as well as the studies referred to for choosing these parameters. In cases we were not able to obtain all relevant (technical) information from the studies or the manufacturer's websites, we contacted the manufacturers. We report instances as n/a if we were unable to acquire the appropriate information. For devices with an adjustable logging interval, it was set as the smallest one used in prior studies with the same devices for our data acquisition. Furthermore, a finer (1-minute) than default (5-minute) logging interval was chosen for the Vivior Monitor to enable resampling of all devices' data at 2 minutes for data analysis (see Table 3.3 & chapter 3.2.2.1). Ethical approval was obtained from the local ethics board at TU Dortmund University, and the study adhered to the tenets of the Declaration of Helsinki.

One experimenter (AH) simultaneously wore the light meters in a field setting during the day. Since both Clouclip and Vivior Monitor are worn on the right side of spectacles, we could not include both devices in the same data acquisition. Thus, data was acquired on two days, with Clouclip worn on the first and Vivior Monitor on the second day. All other devices were worn on both days. Figure 3.3 displays how the devices were worn. Data acquisition started prior to 08:30h and ended after 20:30h on both days. During data acquisition, the experimenter logged the start and end of all activities as well as the times of environment changes from indoor to outdoor and vice versa. Furthermore, she always kept the devices uncovered and it was pre-determined that at least three hours (i.e., 1/4 of the time between 08:30h and 20:30h) would be spent outdoors on each day during at least four different occasions prior to sunset.

The data acquisition was conducted on September, 5, 2022 (Clouclip worn; day 1) and September 6, 2022 (Vivior Monitor worn; day 2) in the City of Dortmund, Germany. On day 1, it was sunny, with temperatures between 18 and 29 °C. On day 2, it was sunny with minimal clouds, with temperatures between 20 and 30 °C (Time and Date AS). Sunrise and sunset times were 06:50h and 20:06h for day 1, and 06:51h and 20:04h for day 2, respectively (sunrise-and-sunset.com).

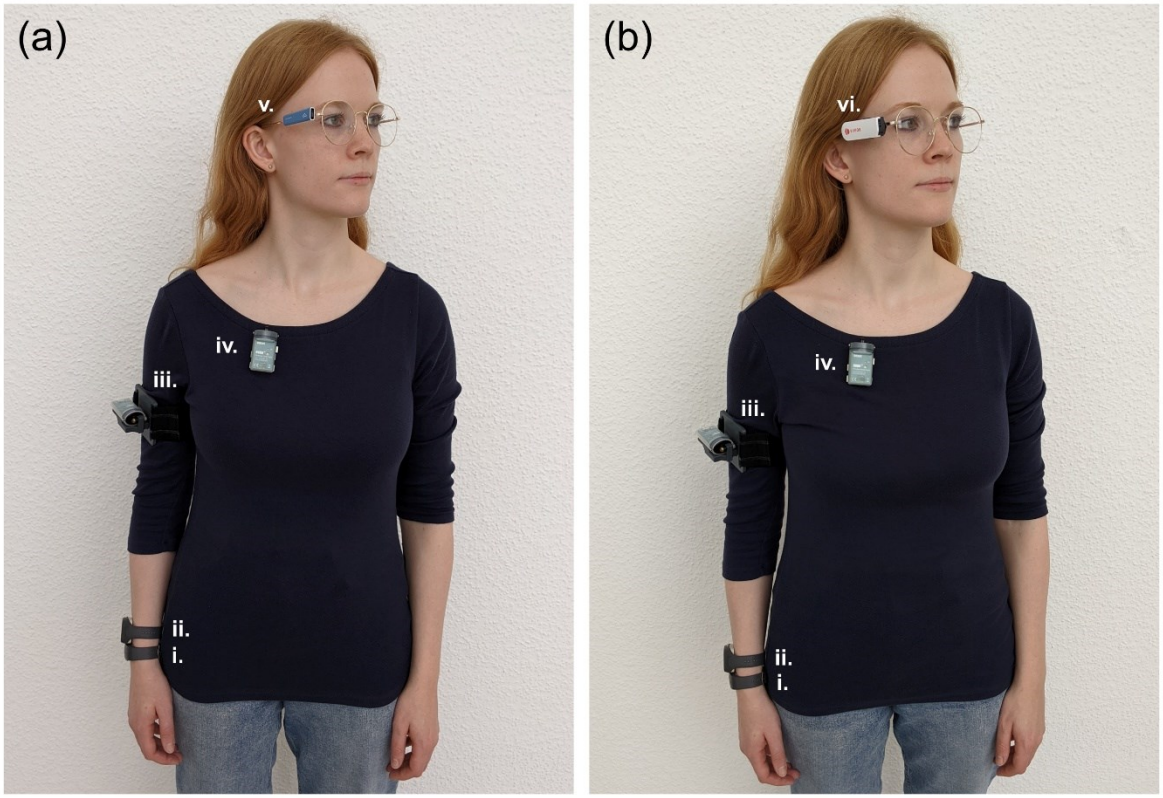


Figure 3.3. Light meter positions on (a) day 1 and (b) day 2 of data acquisition.Devices: i. Actiwatch 2, ii. Actiwatch Spectrum PRO, iii. HOBO Pendant UA-002-64 (attached on pedestal), iv. HOBO Pendant UA-002-64 (attached on collar), v. Clouclip M2, vi. Vivior Monitor.

Table 3.3

Overview of Measurement Devices Used in This Study

device	body location	logging interval	technical features	considered studies	comments
Actiwatch 2 (Philips Respironics, Murrysville, PA, USA)	non-dominant wrist	instantaneous* light exposure recorded every 30 s	- measurement range: 5-100,000 lux - spectral response: 400-900 nm, peak: 570 nm (Koninklijke Philips N.V., n.d.–a)	Flanagan et al. (2020); Franklin (2020); Read et al. (2014); Ulaganathan et al. (2019b)	In the studies referred to, the device was either worn on the non-dominant wrist or the side was not specified or not restricted. All studies cited here used a logging interval of 30 s.
Actiwatch Spectrum PRO (Philips Respironics, Murrysville, PA, USA)	non-dominant wrist	light exposure logged every 30 s, averaged from shorter sampling frequency†	- measurement range: n/a - spectral response: 400-700 nm (Koninklijke Philips N.V., n.d.–d) / 380-750 nm (Koninklijke Philips N.V., 2019); peak: n/a	Abbott et al. (2018); Burfield et al. (2019); Chan et al. (2016); Gordon-Shaag et al. (2021); Harb et al. (2016); Mirhajianmoghadam et al. (2021); Ostrin (2017); Ostrin (2018); Ostrin et al. (2018); Ostrin et al. (2019)	Studies that used either the Actiwatch Spectrum, Actiwatch Spectrum Plus, or Actiwatch Spectrum PRO were considered. In the studies referred to, the device was either worn on the non-dominant wrist or the side was not specified or not restricted. All cited studies used logging intervals of 1 min or 30 s, though it is sometimes only implied and not explicitly stated.

Table 3.3 – Continued

Overview of Measurement Devices Used in This Study

Clouclip M2 (Hangzhou JingZhiJing Technology Co. Ltd., Hangzhou, China)	right side of spectacle frame	light exposure logged every 2 min, averaged from shorter sampling frequency (Hangzhou JingZhiJing Technology Co., Ltd., personal communication, 2023)	- measurement range: 1-65,528 lux - spectral resonse: ca. 400-760 nm; peak: ca. 540 nm (Hangzhou JingZhiJing Technology Co., Ltd., personal communication, 2022)	L. Li et al. (2020); M. Li et al. (2021); Wen et al. (2019); Wen et al. (2020)	
HOBO Pendant UA-002-64 (Onset Computer Corp., Bourne, MA, USA)	- 1x attached near collar with safety pins, facing forward - 1x on custom-built pedestal based on Alvarez (2012), mounted around upper arm pointing skyward	instantaneous light exposure recorded every 10 s	- measurement range: 0-320,000 lux (smaller resolution steps at low than high light levels) - spectral response: ca. 150-1,200 nm, peak: ca. 900 nm (Onset Computer Corporation, 2012)	Alvarez (2012); Alvarez and Wildsoet (2013); Backhouse et al. (2011); Dharani et al. (2012); Schmid et al. (2013); Wu et al. (2018)	In some previous studies, HOBO Pendant UA-002-08 was used. The only difference between the devices is the higher memory capacity of the HOBO Pendant UA-002-64. The logging interval was either 10 s or 5 min in the studies referred to.

Table 3.3 – Continued

Overview of Measurement Devices Used in This Study

Vivior Monitor (Vivior AG, Zurich, Switzerland)	right side of spectacle frame	light exposure logged every 1 min, averaged from sampling frequency of 0.5 s (Vivior AG, personal communication, 2022)	- measurement range: 0-100,000 lux (graphical display 0-10,000 lux, export and statistics include full range) - spectral response: ca. 360-1,100 nm (forward oriented sensor – all channels); ca. 400-800 nm, peak: ca. 530 nm (forward oriented sensor – lux estimation) (Vivior AG, personal communication, 2022, 2023)	Mrochen et al. (2020); Tanrıverdi et al. (2019)	Per default, light exposure data is provided every 5 min. The 1 min scoring was done manually by Vivior AG.

Note. * No confirmation could be obtained from the manufacturer, but other publications (e.g., Read et al., 2015; Ulaganathan et al., 2017) and own observations indicate instantaneous measurements. † No confirmation could be obtained from the manufacturer, but other publications (with Actiwatch Spectrum & Spectrum Plus; Bhandari et al., 2021; Mirhajianmoghadam et al., 2021; Ostrin et al., 2017) and own measurements with Actiwatch Spectrum PRO indicate averaging over a shorter sampling frequency. The sampling frequency is often stated as 32 Hz for both light & activity data (e.g., Bhandari et al., 2021; Ostrin et al., 2017), but on the manufacturer's website, 32 Hz is explicitly given as the accelerometer sampling rate for all Actiwatches, with no indication of the light sampling rate (Koninklijke Philips N.V., n.d.–a, n.d.–b, n.d.–c, n.d.–d).

3.2.2.1. Data Analysis

Data analysis was performed in Jupyter Notebook with Python 3.9.12. Data from 08:30h-20:30h was analyzed. Analyses were initially conducted at different logging rates: Once with the one used for data acquisition, and once with every device's data (re)sampled at 2 minutes as a measurement frequency of 2 minutes (or finer) has been found to provide the most reliable outdoor light exposure measures in an investigation using the Actiwatch 2 (Ulaganathan et al., 2017). To stay in line with the respective devices' way of sampling, those with instantaneous light logging were resampled by using every n^{th} logging entry. Those with data logged as an average from a higher sampling frequency were resampled by averaging the values over 2 minutes each. Since little differences were detected between the analyses of the original and the 2-minute logging rates, only the latter are reported here. Results of the analyses with the original rates are included in Supplementary Table D1-D3. We did not conduct any further data pre-processing like artifact removal.

For day 1, 2 minutes (0.3%) of data from four different timepoints are missing for Actiwatch Spectrum PRO for the original logging, and 8 minutes (1.1%) of data are missing for the resampled logging. For Clouclip, 42 minutes (5.8%) of data from 13 different timepoints data are missing for both logging rates. While we do not know why the Actiwatch Spectrum PRO did not record light data for these brief periods of time, the missing Clouclip data was most probably caused by the device going into sleep mode. The utilized version of Clouclip (M2) does so if no movement is detected for 40 seconds – until movement is detected again, but for at least 2 minutes (Bhandari et al., 2021). No other data is missing for any day or device.

Means and standard deviations per day were calculated for all devices overall, and for protocolled indoor and outdoor times separately. We determined sensitivity (i.e., percentage of actual outdoor time correctly identified by ≥ 1,000 lux) and specificity (i.e., percentage of actual indoor time correctly identified by < 1,000 lux) of the 1,000 lux cut-off for discriminating indoor and outdoor environments for all devices, again for both days. Furthermore, via ROC (receiver operating characteristic) curve analysis, the best cut-off for each device and day was determined by maximizing the sum of sensitivity and specificity.

3.2.3. Results

3.2.3.1. Variability of Mean Lux Values Between Devices and Days

Mean and standard deviation of the measured lux values are presented per device per day in Table 3.4, both overall and split into protocolled indoor and outdoor times. These values varied greatly between devices: For example, the overall mean ranged from 934 lux

(Actiwatch Spectrum PRO) to 6,921 lux (HOBO Pendant UA-002-64 attached on collar) on day 1, and from 422 lux (Actiwatch Spectrum PRO) to 8,039 lux (HOBO Pendant UA-002-64 attached on pedestal) on day 2. Similarly, the devices differed substantially with regard to their indoor and outdoor mean values.

Furthermore, there was variability in the mean values between the two days for the four devices worn on both. This is not surprising, since weather conditions as well as activities and outdoor times were not similar between days. Interestingly though, the devices worn on both days varied in their differences between the days: For both Actiwatches, the overall, indoors and outdoors mean values were lower on day 2 than day 1. Albeit by a much smaller magnitude, the same was true for the indoor means for both HOBO Pendant UA-002-64 devices – but their overall and outdoor mean values were higher on day 2 than day 1. Thus, while one would infer from the Actiwatches' data that the experimenter was generally exposed to brighter light on day 1 than day 2, one would come to the opposite conclusion when considering the HOBO values.

3.2.3.2. Indoor Versus Outdoor Mean Lux Values

As expected, the mean values measured outdoors were always higher than those indoors, although the magnitude of difference varied greatly between devices. Also, all indoor mean values lay below the commonly applied 1,000 lux indoor-outdoor cut-off and all outdoor mean values but that of the Actiwatch Spectrum PRO on day 2 exceeded it (see Table 3.4).

Table 3.4

Means and Standard Deviations of Lux Measurements per Device per Day

device	overall	indoors	outdoors
	day 1		
Actiwatch 2	1,319 (4,215)	674 (3,036)	2,829 (5,877)
Actiwatch Spectrum PRO	934 (3,449)	827 (3,973)	1,186 (1,623)
HOBO Pendant (collar)	6,921 (23,227)	997 (3,365)	20,799 (38,755)
HOBO Pendant (pedestal)	5,762 (16,476)	782 (2,985)	17,429 (26,311)
Clouclip M2	1,303 (3,239)	405 (835)	3,331 (5,166)
	day 2		
Actiwatch 2	929 (3,034)	274 (990)	2,403 (4,959)
Actiwatch Spectrum PRO	422 (595)	175 (254)	970 (749)
HOBO Pendant (collar)	8,011 (28,166)	955 (1,783)	23,902 (46,992)
HOBO Pendant (pedestal)	8,039 (30,383)	732 (2,009)	24,495 (51,011)
Vivior Monitor	715 (1,221)	154 (150)	1,959 (1,581)

Note. All values are given as mean (standard deviation). HOBO Pendant refers to HOBO Pendant UA-002-64.

3.2.3.3. Variability of Maximum Lux Values

No ceiling effect in the measurements was detected for the devices with a known measurement range (see Table 3.3), since none of them reached its upper end – despite the very bright weather conditions on both days. On day 1, the maximum values varied between 35,396 lux (Clouclip) and 176,357 lux (HOBO Pendant UA-002-64 attached on collar). On day 2, they ranged from 3,553 lux (Actiwatch Spectrum PRO) to 198,401 lux (both HOBO Pendant UA-002-64 devices). The low maximum value of the Actiwatch Spectrum PRO on day 2 compared to the other devices as well as day 1 (44,692 lux) is noticeable. Data inspection

revealed that the Actiwatch Spectrum PRO seldomly measured values > 3,500 lux on day 1 as well, doing so only on a few occasions in the afternoon and early evening: As can e.g. be seen in Figure 3.4, only some of the highest peaks between ca. 15:30h and 18:30h in this device's data exceeded said value. The Actiwatch 2, which was worn adjacent to the Actiwatch Spectrum PRO, also recorded a lower maximum value on day 2 (28,158 lux) versus day 1 (41,584 lux), but the extent of the difference is much smaller. Generally, it seems unlikely that this surprisingly low maximum value of the Actiwatch Spectrum PRO on day 2 was a result of measurement complications, especially since the experimenter made sure to keep the sensors uncovered at all times. The overall rather low lux measurements of this device will be discussed further in chapter 3.2.4.

3.2.3.4. Patterns and Absolute Values of Lux Measurements Over Time

The lux measurements of all devices on both days are displayed over time in Figure 3.4, revealing that while the measured values of the individual devices followed a generally similar pattern, there were huge differences between their absolute values, which sometimes even considerably exceeded 100,000 lux.

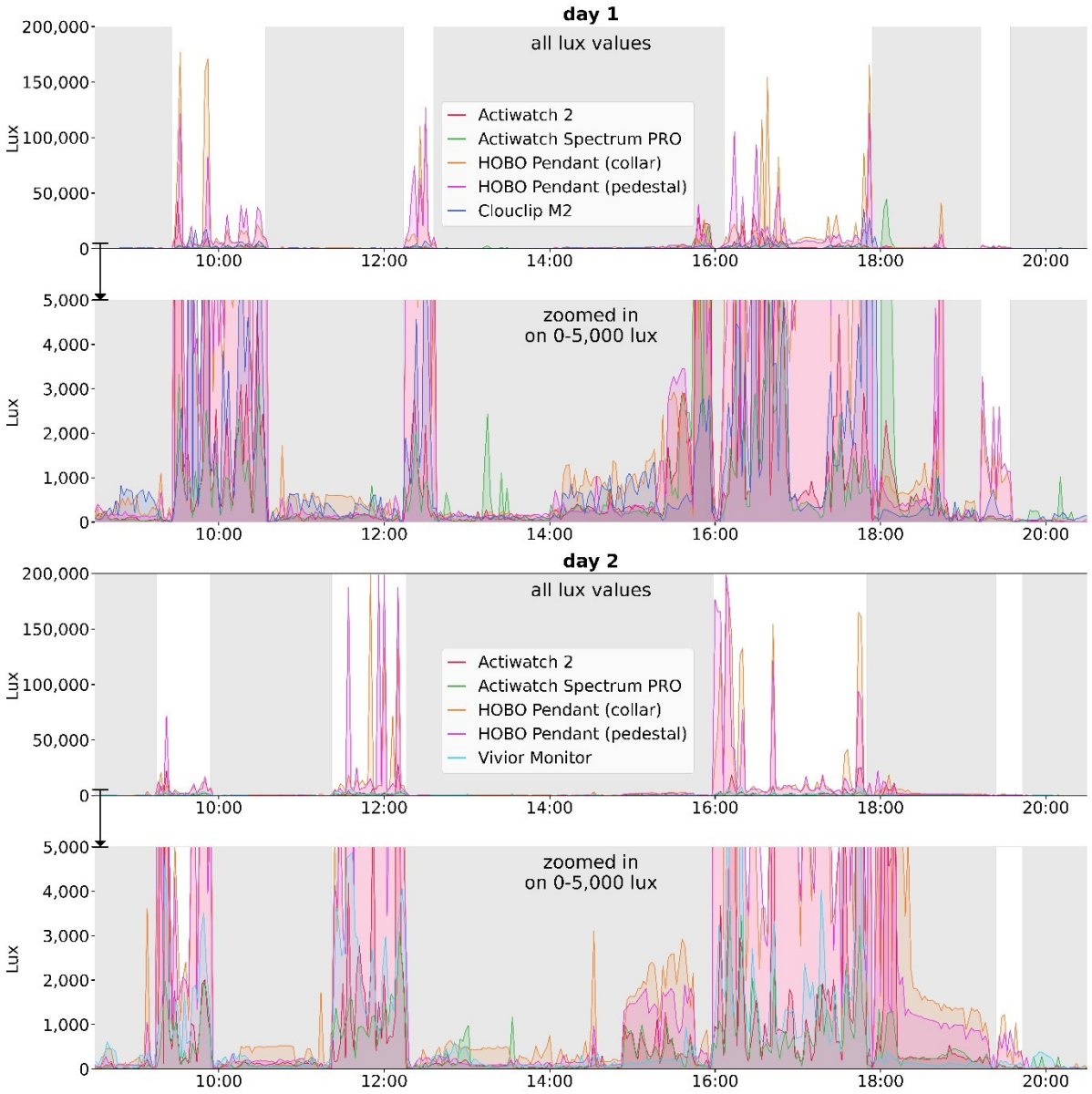


Figure 3.4. Lux measurements of all devices plotted over time for both measurement days. Gray (white) background indicates protocolled indoor (outdoor) location. Each day's top plot displays the complete range of measured lux values. The respective bottom plot displays the lower lux values (0-5,000 lux) at a higher resolution, as indicated by the black arrow between the top and bottom plots.

3.2.3.5. Visual Assessment of the 1,000 Lux Cut-Off

To better represent the devices' measured values both in the range of low and high lux levels, we present their lux measurements for each day on a log scale, both for the devices separately as well as together. While Figure 3.5 provides examples for the classification of indoors versus outdoors by the gray horizontal line indicating said cut-off, Figure 3.6 and Figure 3.7 present the devices' measured lux values for day 1 and 2, respectively.

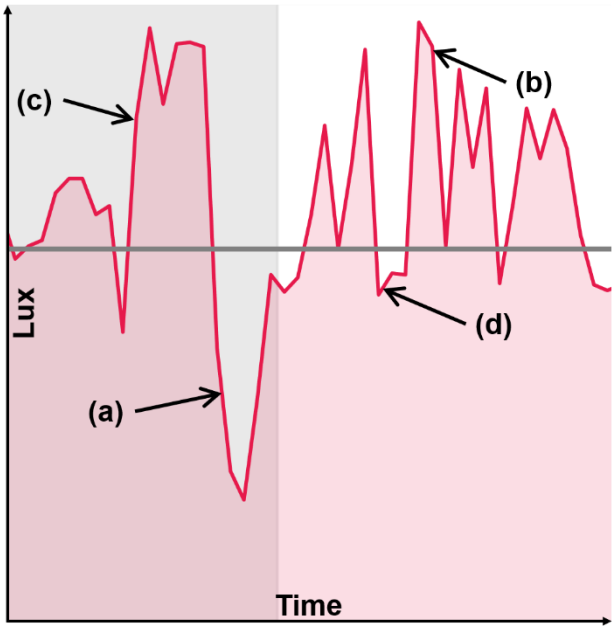


Figure 3.5. Exemplary correct and incorrect indoor and outdoor classifications for Figure 3.6 and Figure 3.7 (cut-out from Figure 3.6). The red line indicates measured lux values, gray (white) background indicates protocolled indoor (outdoor) location. The gray horizontal line is drawn at 1,000 lux. The exemplary classifications by the 1,000 lux cut-off are as follows: (a) correctly classified as indoors, (b) correctly classified as outdoors, (c) incorrectly classified as outdoors, (d) incorrectly classified as indoors.

Therein, it is readily apparent that the readings of all devices exceeded 1,000 lux substantially more often outdoors than indoors – but also that the times and frequencies at which classification would be correct based on this cut-off vary between devices. Furthermore, the figures show that a correct classification of all measured values based on a single lux criterion is hardly possible: For each device there were values recorded indoors that exceeded values recorded outdoors. As would be expected, this is primarily – but not exclusively – the case when having been outside towards evening (last outside time on both days) or for indoor activities near windows. For example, on day 1, the experimenter spent time near a window from 15:24h-15:56h and from 18:00h-18:29h. The same was true for 17:58h-19:19h on day 2. Ignoring such periods would markedly reduce the amount of these overlaps, but would hardly be realistic for a normal daily routine.

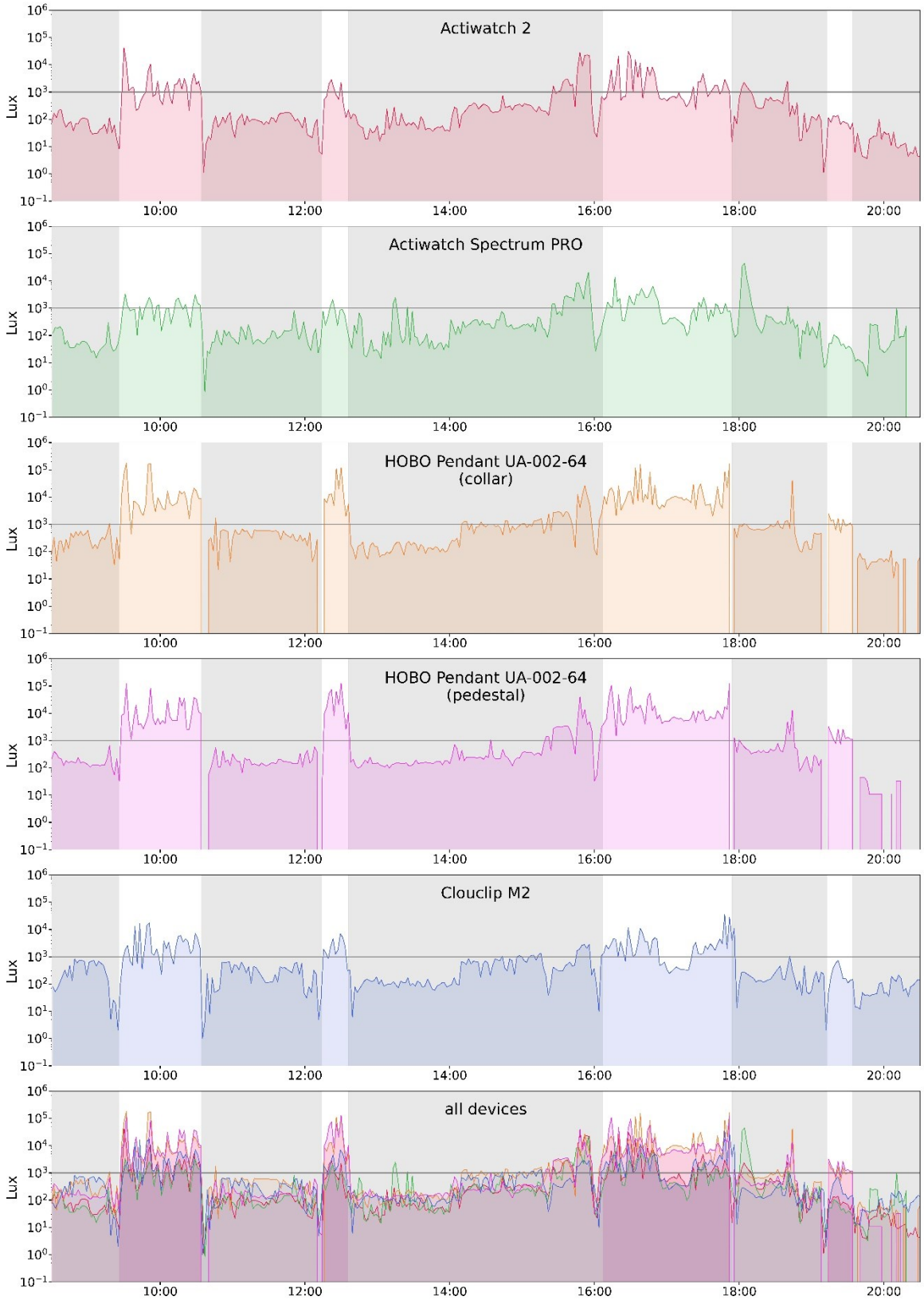


Figure 3.6. Log-scaled lux measurements plotted over time for day 1. Gray (white) background indicates protocolled indoor (outdoor) location. The gray horizontal line is drawn at 1,000 lux. This cut-off results in a correct classification of the environment whenever the device's graph falls below this line in front of a gray background and exceeds it in front of a white background.

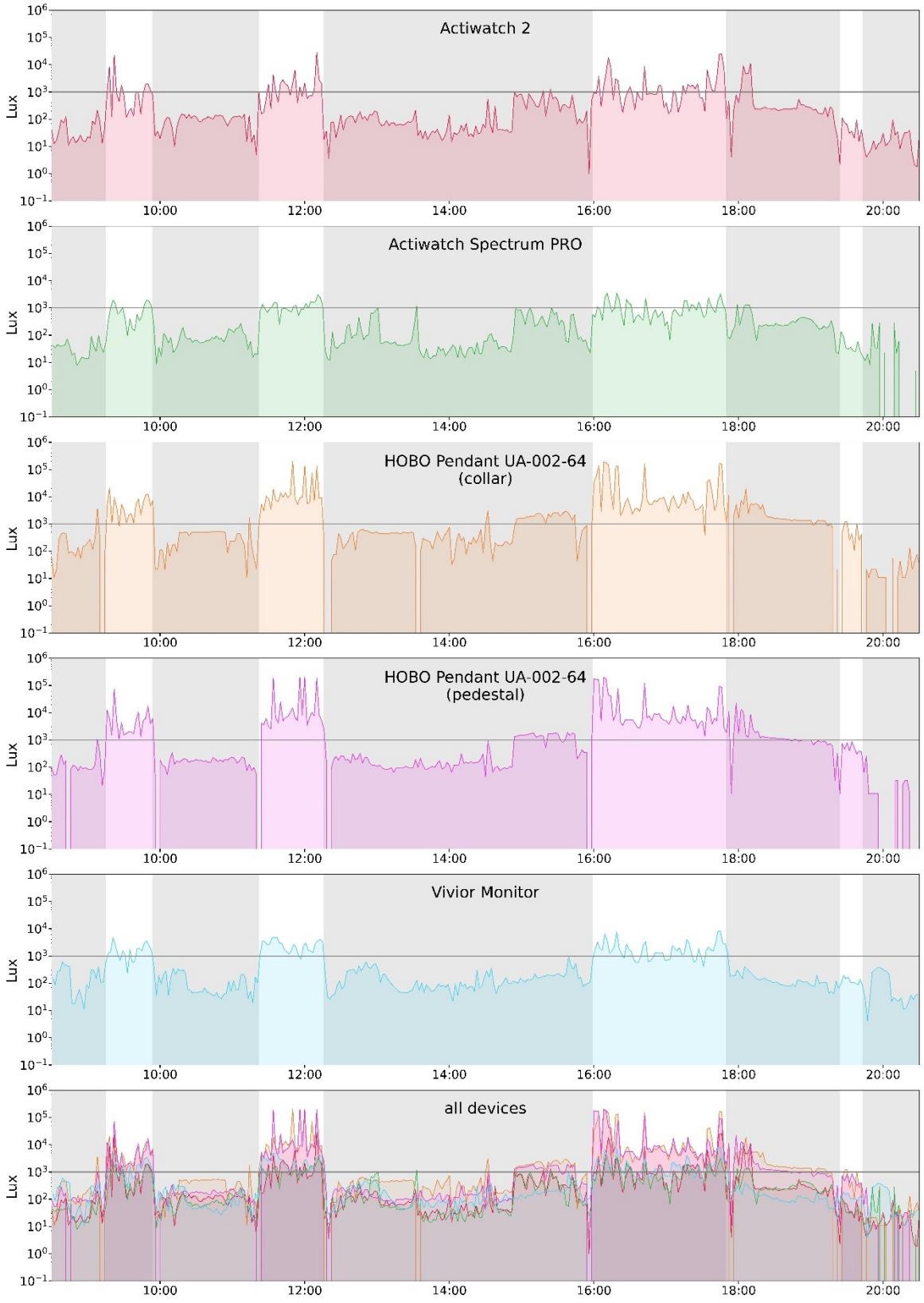


Figure 3.7. Log-scaled lux measurements plotted over time for day 2. Gray (white) background indicates protocolled indoor (outdoor) location. The gray horizontal line is drawn at 1,000 lux. This cut-off results in a correct classification of the environment whenever the device's graph falls below this line in front of a gray background and exceeds it in front of a white background.

3.2.3.6. The 1,000 Lux Cut-Off Sensitivity and Specificity: Magnitude and Variability

Sensitivity (correct classification of actual outdoor time as outdoors) and specificity (correct classification of actual indoor time as indoors) of the 1,000 lux cut-off for each device and day can be seen in Table 3.5. Over all devices and both days, the sensitivities varied between 35.7% and 96.3%, and the specificities between 72.0% and 99.6%. Furthermore, some devices showed a higher sensitivity than specificity, and others vice versa – thus, some were better at correctly recognizing outdoor time than correctly recognizing indoor time and vice versa. For example, both Actiwatches exhibited sensitivities of < 50% and specificities of > 90% on both days. Thus, with the 1,000 lux cut-off, more than 50% of the time spent outdoors was incorrectly classified as indoors, while only less than 10% of the time spent indoors was incorrectly classified as outdoors. Conversely, the HOBO Pendant UA-002-64 (collar) had a sensitivity of 91.2% and a specificity of 72.0% on day 2, thereby exhibiting a reverse – albeit less extreme – pattern. Potential between-device differences like this should be kept in mind when comparing indoor and outdoor times measured with different devices, even – or especially – if the cut-off was kept the same.

Table 3.5

Sensitivity and Specificity of the Environment Classification With the 1,000 Lux Cut-Off and Each Device's Determined Best Cut-Off

	1,000 lux cut-off		best cut-off		
device	**sensitivity**	**specificity**	**cut-off (lux)**	**sensitivity**	**specificity**
day 1					
Actiwatch 2	49.1%	91.7%	460	79.6%	86.6%
Actiwatch Spectrum PRO	40.6%	90.4%	260	81.1%	74.0%
HOBO Pendant (collar)	93.5%	83.0%	1380	91.7%	90.9%
HOBO Pendant (pedestal)	96.3%	88.9%	1050	96.3%	89.7%
Clouclip M2	69.2%	92.8%	840	71.1%	91.5%
day 2					
Actiwatch 2	45.0%	97.2%	370	75.7%	88.8%
Actiwatch Spectrum PRO	35.7%	97.6%	310	83.0%	85.1%
HOBO Pendant (collar)	91.9%	72.0%	2590	81.1%	93.6%
HOBO Pendant (pedestal)	90.1%	78.0%	1900	83.8%	96.4%
Vivior Monitor	72.3%	99.6%	550	90.2%	98.4%

Note. The best cut-off was determined for each device and day by maximizing the sum of sensitivity and specificity via ROC curve analyses. HOBO Pendant refers to HOBO Pendant UA-002-64.

3.2.3.7. Best Cut-Offs From Maximizing Sum of Sensitivity and Specificity

Table 3.5 also presents the best cut-offs for each device and day, calculated by maximizing the sum of sensitivity and specificity via ROC curve analyses. There are, of course, other approaches to obtain the best cut-off as well, and choosing one ideally depends on what is deemed important. For example, if one wants to identify as much outdoor time as

possible, even at the cost of misclassifying more indoor times as outdoors, one should choose a cut-off with a high sensitivity while accepting a lower specificity.

The determined best cut-offs varied substantially between devices. In many cases, both the cut-off value and the associated sensitivities and specificities of a device exhibited large differences between the 1,000 lux and the best cut-off. Strikingly, the sensitivities for the Actiwatches on both days increased from < 50% for the former to > 75% for the latter. Logically, the associated specificities decreased somewhat, but by a much smaller magnitude: While the Actiwatches' sensitivities were between 30.5% and 47.3% higher for the best cut-off than for 1,000 lux, the specificities were only between 9.3% and 21.5% lower.

Generally, despite the fact that a clear cut between indoor and outdoor environments based on light intensity alone is hardly possible, it is apparent that high sensitivities and specificities can be achieved for the given environmental conditions: For the best cut-offs, all sensitivity and specificity values were > 70%. Three out of five devices on day 1 and four out of five on day 2 exhibited > 80% for both measures, and HOBO Pendant UA-002-64 (pedestal; day 1) and Vivior Monitor (only used on day 2) even exhibited > 90% specificity and sensitivity. In comparison, the only cases with both measures > 80% for the 1,000 lux-cut off were the HOBO Pendant UA-002-64 devices on day 1.

The best cut-offs also varied between days for the devices deployed on both – even given the relatively similar weather and outdoor light conditions on both days. Importantly, even a rather large difference in the same devices' best cut-offs between days does not imply that the best cut-off calculated for one day would necessarily have low specificity and/or sensitivity in classifying the other day's data.

3.2.3.8. Cut-Off Sensitivity and Specificity Using the Other Day's Best Cut-Off

Table 3.6 shows sensitivity and specificity when using each device's best cut-off of one day to classify the other day's data for the devices used on both days. As can be seen, both sensitivity and specificity were still rather high for all four devices: Again, all values were > 70%, most of them even > 80% or > 90%. Also, using one measurement day's calculated cut-off to classify the other day's data generally led to better sensitivities and specificities (when aiming at maximizing both measures) than using the 1,000 lux cut-off. This was especially the case for the two Actiwatch devices. For the HOBO Pendant UA-002-64 devices, the other day's best cut-off performed better than the 1,000 lux cut-off in three out of four cases as well, though only slightly so. Only for the HOBO Pendant UA-002-64 device mounted on a pedestal on day 1, the 1,000 lux cut-off exhibited a slightly higher sum of sensitivity and specificity than the day 2 best cut-off.

Table 3.6

Sensitivity and Specificity of the Environment Classification of Each Device's Best Cut-Off for the Other Measurement Day

device	sensitivity	specificity
day 1 (classified with device's day 2 best cut-off)		
Actiwatch 2	80.6%	85.0%
Actiwatch Spectrum PRO	76.4%	78.4%
HOBO Pendant (collar)	83.3%	94.1%
HOBO Pendant (pedestal)	89.8%	92.1%
day 2 (classified with device's day 1 best cut-off)		
Actiwatch 2	71.2%	90.8%
Actiwatch Spectrum PRO	83.9%	81.0%
HOBO Pendant (collar)	85.6%	78.8%
HOBO Pendant (pedestal)	90.1%	80.4%

Note. HOBO Pendant refers to HOBO Pendant UA-002-64.

3.2.4. Discussion

In analyzing data from light meters simultaneously worn from morning to evening in an exemplary field setting, we found that while the devices' lux measurements followed a generally similar temporal pattern, their absolute values as well as overall, indoor and outdoor mean values varied substantially. The latter was also the case for the maximally measured lux values. Thereby, no ceiling effect was found in the devices of which the measurement range is known to us. Furthermore, the devices worn on both measurement days varied in their between-days differences: Actiwatch 2 and Actiwatch Spectrum PRO measured higher overall, outdoor and indoor mean lux values on day 1 than day 2, but for both HOBO Pendant UA-002-64 devices, the opposite was true for overall and outdoor mean lux values. Possibly, between-device differences in their technical specifications may underlie this pattern, for example regarding their differing spectral sensitivities (see Table 3.3).

The large discrepancies between the devices' lux measurements are interesting, and the low values of the Actiwatch Spectrum PRO particularly stand out, especially on day 2. Since we only had one device per type, we cannot exclude with certainty that something was defective on individual devices. However, in our opinion, a number of things suggest that the measurements may well have been accurate. For example, the relative variations in intra-

device measurements over both measurement days are very similar for all devices, and there are e.g. high differences between the lux values of the HOBO Pendant UA-002-64 devices and all other devices, not only the Actiwatch Spectrum PRO. With respect to the HOBO Pendant UA-002-64 devices, it should be noted here that their spectral response differs considerably from the other devices in that it ranges much more into both the ultraviolet and infrared spectrum, with a peak sensitivity in the latter. This could explain the extremely high lux measurements of said devices compared to the others in outdoor settings, as the wavelengths of sunlight extend into both these spectra. With regard to the Actiwatch devices, both of them measured markedly lower lux values on day 2 than on day 1. While there is not much data on the Actiwatch Spectrum PRO or other devices of the same series, (large) measurement differences between the Actiwatch 2 and other devices have been found before. For example, the Actiwatch 2 has exhibited a lower empirically derived cut-off corresponding to photometer-measured 1,000 lux than the Clouclip (533.15 lux vs. 850 lux; Howell et al., 2021) as well as a 4,677±11,048 lux mean difference in light exposure compared to the HOBO Pendant UA-002-64 in data from ten adults who simultaneously wore both devices for one hour (Read, Vincent, et al., 2018). Actiwatch 2 also (linearly) underestimated lux compared to a photometer, especially in high light intensities – with the Actiwatch 2 output being about 30% of the photometer output under LED illumination (Figure 2d in Joyce et al., 2020) and about 40-50% for sunlight measurements (Figure 3f in Joyce et al., 2020; Joyce et al., 2020). The Actiwatch Spectrum Plus, which is mostly similar to the Actiwatch Spectrum PRO and includes the same light sensor, measured a systematically lower light exposure (mean: 215 lux) compared to the Clouclip (mean: 347 lux), when both were worn by adults for a week (Bhandari et al., 2021). Visual inspection of data published by their manufacturer shows that Actiwatch Spectrum – the predecessor model of the Actiwatch Spectrum PRO – and Actiwatch 2 measurements not only deviated from photometer measurements in different lighting conditions, but also from each other, with the direction and intensity of deviations varying between various lighting conditions. In sunlit and outside situations, both devices measured lux values that were – sometimes considerably – lower than the values measured by a photometer (Koninklijke Philips N.V., 2008). Thus, while faulty measurements of individual devices can of course not be ruled out with certainty, the presence of large deviations between all devices and prior data suggest that the generally large differences in lux measurements we found are, in fact, valid.

For all devices, a large distinction between the measured indoor and outdoor mean lux values is apparent, though the magnitude of this distinction varies between devices. Still, all indoor mean lux values lay below the commonly applied 1,000 lux cut-off to distinguish indoor from outdoor environments, and the opposite was true for all outdoor mean lux values except that of the Actiwatch Spectrum PRO on day 2. Also, the lux measurements plotted over time in Figure 3.6 and Figure 3.7 show that all devices' measurements exceeded 1,000 lux

substantially more often outdoors than indoors and vice versa, but times and frequencies of a correct indoor-outdoor classification with this cut-off again varied between devices. The same applies to the devices' sensitivity and specificity for this cut-off: Some devices exhibited a higher sensitivity than specificity, others vice versa. The relation of sensitivity and specificity also relates to whether a device generally over- or underestimates outdoor or indoor time, which is, for example, relevant when assessing participants' total time spent outdoors or indoors. However, this estimation of time spent in either environment not only depends on correctly, but also incorrectly classified times, so whether there is a general over- or underestimation of time spent outdoors or indoors additionally depends on the relation of time actually spent in either environment. Thus, in addition to sensitivity and specificity, it is important to consider the (expected) actual time participants spend in either environment when attempting to estimate whether one is more likely to overestimate or underestimate total time indoors or outdoors with a particular device.

Due to all this, it is not surprising that the best cut-offs, calculated by maximizing the sum of sensitivity and specificity, vary between devices and from 1,000 lux – and e.g. even lie below 500 lux for both Actiwatches on both days. This is not the first time that rather low lux values have been found to be the best cut-offs for distinguishing indoors versus outdoors. For example, two investigations measuring light levels in pre-school children with a hip-worn ActiGraph GT3X+ device determined 240 lux (Flynn et al., 2014) and 110 lux (Tandon et al., 2013) as best cut-offs. Even though both measurement settings and devices in these investigations differed from those of the present study and we are not aware of any myopia-related investigations with light meters worn at hip, it is interesting to consider these findings together, especially since placement at hip and wrist may not be that different for activities like walking, which was the main outdoor activity performed in our study. Regarding the individual cut-offs' performance in our study, the sum of sensitivity and specificity is often markedly higher for the determined best cut-offs than for 1,000 lux – the former exhibiting very high sensitivities and specificities for some devices. Vivior Monitor even exceeds 90% for both measures. Importantly, when using the other day's best cut-off for the devices having been used on both days, both sensitivity and specificity are – apart from one case – still increased compared to the 1,000 lux cut-off. The advantage of the other day's best cut-off over the 1,000 lux cut-off is especially marked for both Actiwatch devices. It was also present, albeit only slightly, in three out of four cases for the HOBO Pendant UA-002-64 devices.

Our data demonstrates that at least for some devices, a lux indoor-outdoor cut-off calculated via maximizing sensitivity and specificity from measurements under similar circumstances as the actual data acquisition can substantially outperform the common 1,000 lux cut-off. Thus, when wanting to distinguish indoor from outdoor environments via lux measurements, it may be helpful to conduct additional measurements with the respective (type of) device under similar conditions than during the data acquisition. This could be

achieved by conducting the additional measurements at the same time and with a similar device as the actual data acquisition. Based on these additional measurements, one could calculate the best cut-off for the given device and circumstances, either by maximizing the sum of sensitivity and specificity or focusing on whichever measure one deems more important. Then, instead of using the 1,000 lux cut-off, which is frequently applied without prior testing for the given device and environment and only justified as having been used in other investigations (which were often conducted with different devices or in different environments), this calculated best cut-off could be used to classify the actual data. Here, we found that this approach can be especially helpful for data acquisition with the Actiwatch 2 and Actiwatch Spectrum PRO. More methodological research is needed to assess for which other devices and circumstances of data acquisition this might also be the case.

Even though high sensitivities and specificities have been achieved with a calculated best cut-off for a number of devices, it is hardly possible to choose a lux cut-off perfectly classifying indoor and outdoor environments and it may be helpful to take other (additional) measurements into account. Even when only considering daytime, in every data acquisition lasting for more than a few hours there will most probably be times at which the indoor illuminance is higher than the outdoor illuminance at some other time. This can, for example, be seen in Figure 3.6 and Figure 3.7, and as is described in chapter 3.2.3, times spent near windows or outside close to the dark are especially critical with regard to a lux-based cut-off. If one aims for an indoor-outdoor distinction based on wearable device measurements that is as accurate as possible – for example, because one is interested in aspects of outdoor exposure other than bright light exposure that may be relevant regarding myopia development (Howell et al., 2021) –, one may thus consider using other measures instead of or in combination with lux, for example ultraviolet (UV) light exposure. Of the devices included here, only Vivior Monitor measures UV light. Similar analyses as for lux revealed a sensitivity of 93.8% and a specificity of 90.3% for the best UV light cut-off – showing that UV light may indeed be a promising measurement to differentiate indoors from outdoors. However, while these values exceed those of most devices' lux measurements in the present study, their sum does not exceed that of the same device's sensitivity (90.3%) and specificity (98.4%) for its best lux cut-off. Combining lux and UV light data may especially be useful to achieve an even more accurate distinction. In fact, there have recently been efforts in this regard. For example, the Akeso device (Fan et al., 2022) apparently classifies indoors versus outdoors based on both lux and UV light data, and for a device named Mumu, the support vector machine algorithm for said classification is based on lux, UV light, and step data (Ye et al., 2019). In general, including other measures such as UV light in the indoor-outdoor distinction seems to be a promising approach that is implemented more and more.

On the other hand, if one is rather interested in times spent in brighter versus less bright environments, roughly corresponding to outdoor- and indoor-like light, it is not as important that any given lux cut-off might incorrectly classify the environment sometimes. What would be problematic in either case though is to assume that lux measurements from different devices, or the same cut-off for different devices (and environments), will mean the same. This is especially the case because it seems that if children spend a lot of time outdoors, exposure to moderate light intensities of e.g. ≥ 1,000 lux or ≥ 3,000 lux (measured with HOBO Pendant UA-002-08) may be sufficient for the protective effect of light exposure on myopia development (Wu et al., 2018). Findings such as this can have practical implications for recommendations, suggesting that direct exposure to bright sunlight may not be necessary for myopia prevention. In order to investigate such quantifications with different devices, it is important to be aware of the potential limits to the comparability of their lux measurements. In this regard, it has not only been shown that different devices' measurements differently deviate from those of a photometer (Figueiro et al., 2013; Howell et al., 2021; Joyce et al., 2020), but we have also seen that while measured lux patterns over time are generally similar between various light meters, the absolute values are not, and sensitivity and specificity of the 1,000 lux cut-off, for example, can vary substantially between devices. For example, with this cut-off and in our measurements, especially Actiwatch 2 and Actiwatch Spectrum PRO exhibited low sensitivities of 49.1% and 40.6%, respectively. Respective between-device differences might play a role in the sometimes contradictory results of studies on the association between light exposure and myopia. Such considerations should therefore be taken into account when comparing data collected with different devices or attempting to derive practice recommendations from such data regarding spending time outdoors or in certain light intensities for myopia prevention purposes.

Generally, while some of the observed deviations between different light meters' measurements in the present study may be due to the devices themselves – as such between-device differences have been shown before for several light meters (Figueiro et al., 2013; Howell et al., 2021; Joyce et al., 2020) – a substantial portion of the observed between-device differences might also be attributed to the wearing position. Thereby, one may want to consider what kind of illuminance one (wants to) estimate(s) with such measurements. For example, illuminance reaching the eyes may best be measured with devices mounted near them and oriented at the line of sight. To measure the illuminance in the general orientation of the individuum, devices positioned at the chest and oriented straight ahead may be useful. Wrist-worn devices probably measure ambient illuminance in varying orientations depending on the orientation of the individuum's arm, and skyward ambient illuminance could, for example, be measured with devices mounted with the light sensor oriented upwards. In fact, there are various reports of substantial light measurement deviations between different positions (Aarts et al., 2017; Figueiro et al., 2013; Wen et al., 2021). Some of them, however,

indicate that measurements at chest and eyes do not deviate as strongly from each other as measurements at wrist and eyes. For example, significant differences were found between lux measurement near the eye compared to at wrist, but not compared to at torso or a device worn as a pendant around the neck (Figueiro et al., 2013), and larger illuminance measurement inaccuracies compared to a reference position between the eyes have been reported for measurement at wrist than at the chest (Aarts et al., 2017). Correspondingly, in a review on light dosimetry in field research of non-visual effects of light, placing the device at eye-level for precise measurements, or alternatively at the chest, was recommended (Hartmeyer et al., 2022).

Beyond the focus of this investigation, it is important to note that potential influences of device specifications and position on light measurements are of course not the only relevant factors when interpreting data from or planning investigations using wearable light meters. For example, depending on geographical and climatic conditions, wrist-worn sensors could pose the risk of being covered by clothing – especially because participants might easily forget that they are wearing them due to their low intrusiveness. On the other hand, spectacle-mounted devices may affect participants' behavior in different ways, depending on whether or not they usually wear spectacles. In a study with 5th-grade students wearing Clouclip, myopic participants did indeed reach the required device wearing time more often than emmetropic participants (Wen et al., 2019) – and while a between-group difference in being used to wearing spectacles is not confirmed as the (only) underlying factor for this, it is rather conceivable that it may have played a large role. Therefore, the applicability of devices and wearing positions for the given situation should also always be critically assessed.

There are some limitations to this investigation. For one, we tested a rather restricted field setting, in which situations like using public transport or cars or being in supermarket lighting were not included – instead, data acquisition was restricted to being at home or outside. In the future, investigating other locations, outdoor light conditions, and settings would be informative – since, for example, traveling in vehicles is discussed regarding the indoor-outdoor differentiation as being difficult to identify via light sensor (Flynn et al., 2014). Issues like accidentally covering sensors with clothing that may arise in a real field setting were also not included as we created a setting with a perfectly compliant participant. As mentioned earlier, we only included one device per type. Since between-device variations are known to exist for devices of the same model (e.g., for the Actiwatch Spectrum (Markvart et al., 2015) and the Actiwatch Spectrum PRO (Nagra et al., 2021)), and devices may also malfunction, ideally, more than one device per type should be included in future investigations. The main objective of this investigation was to investigate and illustrate the general between-device variation in lux measurements and indoor-outdoor distinctions. Thus, we believe that the study's findings and conclusions are valid nonetheless. In this context, it is important to interpret the study's results correctly. For example, we derived the

best indoor-outdoor cut-off values per device and demonstrated their between-device variability, deviations from 1,000 lux, and the differences in sensitivity and specificity between them and the 1,000 lux cut-off. These cut-offs should, however, not be interpreted as being the ideal ones for the respective device types and under any circumstances, just because they yielded the best results for these exact devices in the present study's setting. Like for devices, it would also be interesting to include more participants to e.g. investigate how much of a difference the varying cut-offs make in a larger sample – although if the participants do not consist of trained experimenters meticulously logging all activities, one would not have as reliable information on said activities to assess the devices' lux indoor-outdoor cut-offs as we did. Lastly, we only investigated differences and similarities of various light meters regarding their general light measurements as well as indoor-outdoor cut-offs. Further steps may be to convert measured light data to make it comparable to a photometer and/or between devices. This has already been done for some devices, for example by adjusting cut-off criteria for light exposure categories to align with that of a photometer for Actiwatch 2 and Clouclip (Howell et al., 2021), or by using a linear regression model to correct lux output from GENEActiv and Actiwatch 2 to represent that of a photometer (Joyce et al., 2020). Despite these limitations, we gained interesting insights into the comparability of lux measurements from different devices, which should be expanded in the future. Interestingly, one recent dissertation investigated lux measurements from three wearable devices on a larger scale (Phan, 2022). Amongst others, the author compared real-life measurements of Clouclip M2, HOBO Pendant UA-002-64, and Actiwatch 2 from 59 participants. Due to the nature of the experiment, other than ours, this study e.g. did not include the calculation of indoor-outdoor cut-offs based on an accurately kept activity logs – but with regard to lux measurements, the results also show large between-device differences, with particularly the HOBO Pendant UA-002-64 greatly differing from the other devices (Phan, 2022). Results like this show that our findings of large measurement variability between different devices do seem to generalize to a more real-world setting with many participants.

We demonstrated that various light meters worn simultaneously in an exemplary field setting measured a generally similar pattern of light exposure, but varied substantially in their absolute values. Furthermore, while a large portion of all measured outdoor (indoor) lux values lay above (below) the common 1,000 lux indoor-outdoor cut-off, the respective sensitivities and specificities were substantially different between devices – indicating that one cannot assume between-device comparability for this cut-off. The calculated best cut-offs generally varied between devices and often substantially from 1,000 lux, and their sensitivity and specificity values sometimes considerably exceeded those of the 1,000 lux cut-off. Furthermore, the sensitivity and specificity values of the lux indoor-outdoor cut-off calculated as ideal for measurements under similar weather conditions also outperformed those of the 1,000 lux cut-off in almost all cases, sometimes substantially so.

While more research is needed with regard to other devices and data acquisition circumstances, we therefore recommend to consider calculating the best indoor-outdoor cut-off from data acquired with a similar device and under similar circumstances as in the actual data acquisition to achieve the best lux-based indoor-outdoor distinction. Furthermore, aspects of lux measurement comparability should always be carefully assessed when planning or interpreting results from research on the association between light exposure and myopia conducted with wearable light meters.

3.3. Study 6:

A Feasibility Study on the Development of a Wearable Device for Investigating Light-Myopia Associations

Abstract: There are various research applications for wearable devices, one of which is measuring environmental factors involved in myopia development, especially light intensity. To investigate the feasibility of developing and deploying a custom-made device tailored to one's study requirements, here, a wearable device targeted for the research of light-myopia associations in humans was developed and tested. Five device prototypes were built and used for various data acquisitions: device comparison measurements to compare the devices against each other, category and test measurements to assess their performance in different environments as well as potential lux and UV light indoor-outdoor cut-off values, and a 7-day field test with six participants to test the devices in a study-like scenario. We pre-processed and analyzed the field test data with methodology commonly used in myopia research to evaluate if this methodology can be applied to our device data. Overall, the measurements and analyses performed demonstrated the device's feasibility for data acquisition and analyses in relation to light-myopia association research. However, there were some issues regarding mechanical properties and device handling. Actual investigations of light-myopia associations would benefit from further device improvement to resolve said issues as well as to potentially improve device comparability – which was generally satisfactory, but could still be improved. Thus, as there are currently a number of devices commercially available for light-myopia research, using one of those might be more convenient if there is no need of specific measurements that none of these devices offer. However, our research demonstrated that it can be a viable option to develop and use a custom-made device for field studies with humans. Developing a custom-made device for one's research may thus be of special relevance for research areas with fewer (or no) commercially available devices.

3.3.1. Introduction

There are many applications of wearable devices in field studies with human subjects (for reviews, see: Abboushi et al., 2022; Perry et al., 2018), one of them being the measurement of environmental factors that are relevant with regard to myopia development. Initially, an association between myopia and the amount of outdoor activities had been reported in several studies, mostly indicating a protective effect of these activities against myopia development (Jones et al., 2007; Rose, Morgan, Ip, et al., 2008; Rose, Morgan, Smith, et al., 2008). Further research, including human studies with wearable devices, then indicated that the amount of time outdoors – and not sporting activities – seems to be the (more) relevant factor with regard to myopia development (Guggenheim et al., 2012; Guo et al., 2013). As of now, multiple characteristics of outdoor environments have been discussed to play a role in myopia development. While there are e.g. hypotheses regarding the relevance of vitamin D levels or the spectral composition of outdoor light, there is strong evidence for bright light exposure being a key protective factor in myopia development (Morgan et al., 2021).

When studying the involvement of environmental factors in myopia development, it is thus especially important to measure light intensity (lux) with wearable devices. As other factors may also be of relevance – e.g., regarding the protective effect of time outdoors –, using wearable devices not only to measure light intensity, but also to quantify time spent indoors versus outdoors is of interest. The latter is often done with the help of light intensity measurements – namely, by defining a cut-off lux value to distinguish indoor from outdoor locations. Said cut-off is usually set at 1,000 lux across studies and devices without prior validation. This may, however, be problematic, since factors like device specifications or seasons of data acquisition might influence whether 1,000 lux is indeed the best discriminator (Study 4 – Hönekopp & Weigelt, 2023). In some investigations, the indoor-outdoor lux cut-off is chosen or validated with own measurements (Alvarez & Wildsoet, 2013; Schmid et al., 2013; Wu et al., 2018). Especially if one is interested in indoor versus outdoor exposure (rather than simply exposure to less bright versus brighter light), an approach such as this may generally be advisable. In this regard, measuring UV (ultraviolet) light may help in discriminating indoor from outdoor locations – either as a singular factor or in combination with other factors. For example, Fan et al. (2022) describe how a combination of UV light and lux data is used with a device named Akeso eye care glasses to recognize indoor versus outdoor exposure. Lastly, although physical activity is mostly discarded as a factor in myopia development, measuring movement or position change with a wearable device may still be useful in terms of data quality control, e.g. to identify times at which the device had not been worn. Recently, step data has also been used alongside UV light and lux data to discriminate between indoor and outdoor locations (Ye et al., 2019). Thus, measuring light intensity, UV light, and device

movement and/or position can be relevant in investigating light-myopia associations with wearable devices.

One can of course employ already existing devices in studies on light-myopia associations. In fact, there are multiple commercially available options that may be or have been used in this regard (Study 4 – Hönekopp & Weigelt, 2023). However, a purchased device may not entirely fit a study's requirements: Researchers might need to forego certain measurements, or they might need to employ a workaround like using different devices simultaneously. For example, Bhandari et al. (2022) asked participants to wear two devices when investigating associations between myopia and multiple behavioral factors. Research might benefit from having all relevant features combined in one device created to fit the needs of an investigation – not only regarding possible measurements, but also other functionalities like device-experimenter communication. Gathering more information than needed for a study's purpose may be problematic as well for privacy reasons, especially if participants wear the device in their private life. Using commercially available devices that measure more than needed may thus also be undesirable. Lastly, in commercially available devices, not all potentially relevant parameters are always disclosed, and manufacturers might change device specifications (Study 4 – Hönekopp & Weigelt, 2023; Markvart et al., 2015).

Therefore, we developed a wearable device targeted for the research of light-myopia associations in humans. The device was developed parallel to the (literature) research for Study 4 (Hönekopp & Weigelt, 2023) and Study 5. We first defined requirements for the device. Then, five device prototypes were developed and built by two electrical engineers. Subsequently, the prototypes were used for various data acquisitions: We performed device comparison measurements (DCM) to compare our five devices against each other. Then, we carried out category measurements (CM) and test measurements (TM) to assess our devices' performance in different environments, and to assess potential lux and UV light indoor-outdoor cut-off values. Finally, we deployed the devices in a seven-day field test with multiple participants to test them in a study-like scenario.

With this study, we wanted to investigate the extent to which it is possible to develop a wearable device tailored to one's research with reasonable effort. Thus, the objectives of this study are (1) describing the development of our device prototypes and (2) assessing their usability for research on light-myopia associations. For the latter, we assessed their between-device comparability as well as cut-off values for indoor-outdoor distinction as described above. We also pre-processed and analyzed the field test data with methodology commonly used in light-myopia research to evaluate if this methodology can be applied to our devices' data, and assessed the general usability of our prototype based on the results.

3.3.2. Methods

The study was approved by the ethics committee at TU Dortmund University and followed the tenets of the Declaration of Helsinki. All participants provided written informed consent prior participation.

3.3.2.1. Device Requirements

The requirements we set for the device development were as follows:

- able to measure the following:
    - visible light (lux)
    - UV light, ideally close to the range of 200-400 nm
    - movement or position
- wearable in daily life
    - ability to withstand a fall from circa chest height
    - small and lightweight enough for all-day wear, ideally while not being too noticeable
- able to log data with a timestamp, ideally every 30 seconds, minimally every 2 minutes
- splashproof
- charging connection accessible from outside so that participants can charge the device
- battery life minimally 24 hours, but ideally multiple days, as participants might forget to charge the device overnight or the charging might malfunction
- ability to communicate relevant data to the experimenter, e.g. if the device has not been moved for a specified time during data acquisition
- enclosed in a case without sharp edges

3.3.2.2. Device Components and Technical Specifications

Five device prototypes were developed, manufactured and programmed by two electrical engineers, Sean Dalton and Stefan Slooten, as part of a collaborative project. For in-depth information on the device components and technical specifications, please refer to the Github project.[7] The device version from this study is referred to as revision 1.1 therein. Briefly, the following device components are crucial for our investigation:

(a) An ambient light sensor (BH1750FVI-TR, ROHM Semiconductor) is included to measure light intensity. The manufacturers specify a lux range of 1-65,535 lux (16bit sensor; ROHM Co., Ltd., 2014). However, as the raw data from this sensor needs to be divided by 1.2 to receive the lux value (ROHM Co., Ltd., 2014), the default maximum value, which was also the setting for our devices, is 54,612 lux. The measurement range can be adjusted to detect a minimum of 0.11 lux and a maximum of 100,000 lux when adjusting sensor sensitivity (ROHM Co., Ltd., 2014). The sensor's spectral sensitivity is ca. 400-720 nm with peak sensitivity at 580 nm (Fig. 1 in ROHM Co., Ltd., 2014), thus approximately matching that of the human eye.

(b) An UV-A sensor (GUVA-S12SD, Genicom Co., Ltd.) with a spectral sensitivity range of 240-370 nm (Genicom Co., Ltd., 2018) is used to measure UV light. The output of this sensor is photocurrent in nanoamperes (nA). This output can be transformed to e.g. UV index. However, since this would reduce data resolution, and measurements can also be compared regarding intensity in this format, we kept it as photocurrent in this study.

(c) For motion detection, the device includes a 6-axis module combining a 3-axis accelerometer and a 3-axis gyroscope (MPU-6050, IvenSense Inc.; IvenSense Inc., 2013).

(d) Timekeeping and timestamping data is enabled via a real-time clock (PCF8563TS/5; NXP Semiconductors N.V.).

(e) A 16 GB Micro SD card is used for data storage. It can be removed by the experimenter to transfer the acquired data. With an SD card of this size and the current device components, many weeks of data can be stored, even at a measurement interval as fine as 1 s.

(f) A Universal Mobile Telecommunications System (UMTS) Module (SIM800L; SIMCom Wireless Solutions Co., Ltd.) and a Micro-SIM card are built-in to enable data transmission via cellular network. While the acquired data is generally stored on the SD card and read-out by the experimenter after data acquisition, we e.g. use the

[7] https://github.com/S34m1n4tor/health_sense

cellular network to send real-time information about the initialization success to experimenters (see below).

(g) A rechargeable lithium-polymer battery (3.7 V; 1,100 mAh) with a charging connection accessible from outside ensures that participants can charge the devices during data acquisition. With the current device components and specifications (see below for firmware aspects), one day of data can easily be acquired and two days are also possible, but the battery needs to be charged overnight to reliably record data over multiple days.

The components were mounted on a printed circuit board and enclosed in a case (1552C3BK, Hammond Manufacturing) with a custom-made routed opening above the sensors, fitted with UV light permeable 2 mm transparent casted acrylic glass (Acrylglas GS 2 mm, Kunststoffplattenonline GmbH). Since the case was black, we pasted it over with white tape to reduce the risk of overheating.

The device firmware was written in Arduino. While the full code can be accessed online[8], the following aspects with regard to firmware and device functionality are especially relevant for this study:

(a) After connecting the battery, the device setup starts. An SMS is sent to the experimenter phone if the setup is completed correctly.

(b) In case of problems with either date acquisition or the SD card during device setup, a respective SMS is sent to the experimenter phone.

(c) The device was programmed to measure and log the following data every 30 seconds: Year, month, day, hour, minute, second, lux, UV light (nA), gyroscope values (gx, gy, gz), battery voltage.

(d) If there is no movement recorded for 6 hours between 8:00h and 20:00h, an SMS is sent to the experimenter phone. No movement is inferred if the sum of the absolute values of gx, gy and gz is below the threshold of 2,000, which we set via pre-tests. We aimed at choosing a value high enough to ensure that minimal movements (e.g., if the device was not worn, but slightly moved while lying somewhere) would not reset the counter for the time without movement, but also low enough to capture participants' movements if they were relatively still for longer periods of time (e.g., during desk work).

[8] https://github.com/S34m1n4tor/health_sense

For data acquisition, the device was mounted into a soft mobile phone case that can be worn around the arm and is intended to carry one's phone during exercise. In front of the acrylic glass-covered opening of the device's case, we removed the protective foil of the mobile phone case. We also equipped participants with a self-made extension for the mobile phone case band so that it could be worn over heavy clothes. Figure 3.8 shows the device as it is worn on the upper arm.

Figure 3.8. Device worn on the upper arm.

3.3.2.3. Device Comparison Measurements

We carried out the DCM to assess the comparability of the five devices' measurements. To this end, we mounted the devices next to each other on a wooden board (see Figure 3.9), and obtained simultaneous measurements in several static and one moving condition(s). Comparable procedures have been reported before (Ostrin, 2017; Read et al., 2014; Wen et al., 2021). During setup prior to as well as switch off after the DCM, the devices were filmed together with the time measured by an atomic clock to externally validate the recorded date and time.

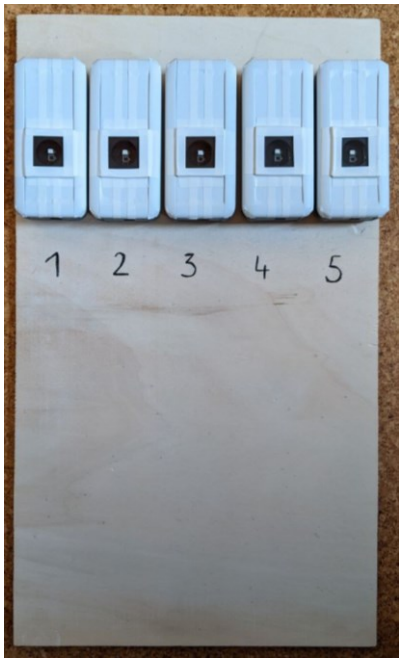


Figure 3.9. Devices mounted on the wooden board for DCM.

For the static DCM, we placed the board in four different conditions with the sensors oriented upwards:

- indoors – with (artificial) light
- indoors – without (artificial) light
- outdoors – (on enclosed) balcony
- outdoors – (under) free sky

We obtained five minutes of measurements per condition while simultaneously measuring with a luxmeter. To mark the measurements' starting and end points, we placed a cloth over all devices simultaneously and kept it there for at least one minute prior to and after each measurement.

For the moving DCM, an experimenter held the board with the sensors facing straight forward, and carried it around outside for 30 minutes to test the devices' comparability under more realistic conditions. Again, the beginning (end) of the measurement was marked by simultaneously uncovering (covering) all devices with a cloth. Furthermore, we omitted the first and last minute of data to ensure that only data while walking was analyzed. We used the results of the DCM to choose three devices for further use in the study (see chapter 3.3.3).

3.3.2.4. Category Measurements

As stated above, we only used three devices for the CM and all following measurements. Procedures comparable to our CM have also been reported before (Dharani et al., 2012; Franklin, 2020). Again, the devices were filmed together with the atomic clock-measured time during setup and switch off. Each device was worn by a different experimenter for 12 minutes in the following pre-defined categories:

- outdoors – free: outdoors, under the free sky
- outdoors – covered: outdoors, not under the free sky but e.g. under trees or a canopy
- indoors – open window: indoors, oriented towards open window
- indoors – closed window: indoors, oriented towards closed window
- indoors – towards window: indoors, oriented towards closed window without standing directly in front of it, e.g. sitting and reading in a chair facing a window
- indoors – regardless of window: indoors, moving in a room with closed window(s) without considering one's orientation, e.g. vacuuming or cleaning
- indoors – away from window: indoors, oriented away from closed window

- indoors – no window: indoors, in a room without windows
- indoors – artificial light: indoors, after sunset with normal room illumination

Apart from "indoors – artificial light", we took all measurements twice, once on a sunny and once on a cloudy day, thus resulting in 17 measurement categories. Furthermore, we began each measurement at the earliest 2 hours after sunrise and ended them at the latest 2 hours prior sunset. As we conducted the CM to initially assess indoor-outdoor discrimination with lux and UV light values, we carried the CM out in May 2021, amidst the two field test data acquisition periods, to best match weather and light conditions of all field test data acquisition periods.

3.3.2.5. Test Measurements

The TM were carried out by the same experimenters as the CM, with each experimenter using a different device than in the latter. The devices were again filmed together with the atomic clock-measured time during setup and switch off. Each experimenter wore their device for one day, from getting up in the morning until going to bed at night, while manually logging each change from indoor to outdoor and vice versa, as well as any times where the device had not been worn or concealed for ≥ 15 minutes. Thereby, we aimed at creating natural control measurements to assess cut-off values for indoor-outdoor discrimination in the field test. The TM were thus also conducted between the field test's data acquisition periods.

3.3.2.6. Field Test

3.3.2.6.1. Participants

Six university students (3 female, 3 male), aged 20.18-27.46 years (*M* = 24.03, *SD* = 2.98) participated in the field test. All participants lived in Dortmund or an adjacent city. During each of the two data acquisition periods (see chapter 3.3.2.6.2), three participants took part during the same days.

3.3.2.6.2. Design and Procedure

Preceding data acquisition, participants attended a pretest at TU Dortmund University, where they answered an online pre-questionnaire on demographic data and ocular history and completed a visual assessment. The latter entailed non-cycloplegic autorefraction (Vision Screener Plusoptix A12R, Plusoptix GmbH, Germany), monocular best-corrected visual distance acuity (LEA symbols 3 m), a covering test to exclude manifest

strabismus, and – if applicable – measurement of the participant's spectacle lenses (TL 3000C, Tomey GmbH, Germany). Since it is irrelevant for this study, the participants' visual health is not reported here. Lastly, we informed participants about correct device usage and safety (e.g., to avoid the device being damaged or underwater and to immediately report any such incidents), and handed out the devices and additional material such as the case band extension and a safety bag for charging. The device was set up by an experimenter prior to the pretest, which was again filmed together with the atomic clock-measured time.

Each of the two data acquisition periods covered seven consecutive days (five weekdays and two weekend days). The first period was 24/04/2021-30/04/2021, and the second period 26/05/2021-01/06/2021. We instructed participants to wear the device from getting up in the morning to going to sleep at night, except when in water or other situations they had been asked to avoid, and to charge it overnight. The device was worn on the upper arm, with the sensors oriented forward (see Figure 3.8). We further asked participants to note any device removal or covering periods of ≥ 15 minutes and report on them in their study diary. Said diary consisted of an online questionnaire that participants were to complete every night, asking about the following:

- bedtime of the previous day
- time of getting out of bed of the present day
- times at which the device had been concealed or not worn for ≥ 15 minutes on the present day
- if they still had the device
- if the device had been in a situation they had been asked to avoid
- any device-related concerns

If participants indicated one or more periods of device non-wear or concealment, they were asked to specify time, location (indoor/outdoor), activity, and reason. If participants indicated that the device had been in a situation they were to avoid or concerns, the questionnaire contained further instructions. Each morning, one experimenter assessed the prior day's diaries regarding the need for intervention – e.g., if a participant had stated a concern or did not fill in the diary.

Following the final day of their data acquisition period, participants completed an online post-questionnaire. Therein, we asked what they thought the device measured, if and how much they had changed their daily routine due to the device, if they had noticed the device in their daily routine, about their sun protection usage (hats/caps and sunglasses, see Read et al., 2014), if the device had been in any situation they had been asked to avoid, and the comparability of their life during data acquisition to three months ago and pre-Covid 19

pandemic times, since data acquisition took place amidst the pandemic. Finally, participants met with an experimenter to return the device and discuss any open questions, and an experimenter switched the devices off, again filming it together with the atomic clock-measured time.

3.3.2.7. Data Analysis

3.3.2.7.1. Device Comparison Measurements

First, we calculated mean and standard deviation for both lux and UV light per device and condition and visually assessed the devices' performance in the different conditions. On this basis, we chose three devices for further use. We then calculated intraclass correlation coefficients (ICCs) for the moving condition as well as the static conditions for the three chosen devices. ICCs are measures of reliability reflecting both correlation (i.e., consistency of position) and agreement (i.e., absolute similarities) between sets of ratings or measurements (Bruton et al., 2000; Koo & Li, 2016). Based on the nature of one's study, one can choose from multiple ICC models. We selected the two-way mixed effects, absolute agreement model for a single measurement (McGraw & Wong, 1996). We chose absolute agreement, since we were interested in the absolute similarity of the devices' measurements, not only if they were consistent in order and spacing (i.e., with potential systematic measurement differences). The mixed rather than random effects model indicates that the devices were not selected from a larger population, but were the only devices of interest (Koo & Li, 2016). Thus, the result cannot be generalized to other, similar devices. Due to the devices being assembled by hand and not within a larger production series, we believed the mixed effects model to be more suitable. However, since the formulas for computing both models are similar if the other model parameters are kept the same, the between-model difference is a question of interpretation, not calculation (Koo & Li, 2016). Lastly, we chose the single measurement ICC type to assess the reliability of one device's rating, as only one device per participant is used in data acquisition.

3.3.2.7.2. Category Measurements

From the CM data, we again computed mean and standard deviation for both lux and UV light for all three devices and all categories. We used this as well as visual data assessment for an initial evaluation of indoor versus outdoor discrimination with a lux or UV light cut-off value.

3.3.2.7.3. Test Measurements

We used the TM data for ROC curve analyses to identify the ideal lux and UV light indoor-outdoor cut-off values by maximizing sensitivity (i.e., percentage of actual outdoor time correctly identified by the respective cut-off value) and specificity (i.e., percentage of actual indoor time correctly identified by the respective cut-off value) – similar to the procedure in Study 5 – for all three devices together. All analyses regarding potential indoor-outdoor cut-off values were performed so that a measured value equal to or greater than the cut-off value indicated outdoors. We did not include TM analyses for each individual device because we wanted to define one cut-off for all devices, and we assumed there was too few outdoor data from each individual device to reliably calculate sensitivity and specificity. We included times between sunrise and sunset in this analysis. We also assessed the frequently used 1,000 lux cut-off.

Prior to the ROC curve analyses, we excluded times during which a device had not been worn for ≥ 15 minutes according to experimenter protocol. We further removed the data one minute prior to and one minute after each protocolled transition from indoors to outdoors or vice versa, to account for potential time measurement differences in the protocolled versus device-recorded time. Lastly, we excluded data from situations that were unclear with regard to being indoors or outdoors to not include ambiguity in cut-off calculations – for example, times where experimenters were situated on an enclosed balcony or driving a car.

3.3.2.7.4. Field Test

3.3.2.7.4.1. Participant Questionnaire Data

To evaluate the feasibility of our devices for field data acquisition, we firstly assessed participants' feedback and device assessment from the post-questionnaire and conversations with the experimenters. This includes information on whether the device had been in any situations that were to avoid, change of daily routine due to the device, noticing the device during daily routine and any device-related open comments as well as participants' assessment regarding the similarity of their current daily routine compared to pre-pandemic times.

3.3.2.7.4.2. Missing Data

With regard to the device data, we first assessed all data for completeness, and found that some data was missing for three participants due to technical device failures. For two participants, the devices had stopped measuring and had started again later during data acquisition, but with a "dummy" date and time instead of the correct one, showing failed date acquisition in the device setups during data acquisition. For the third participant, this was also

the case, but with additional problems regarding the date acquisition in the initial device setup prior data acquisition. With the help of the videos of time measurements at both the devices' setup and switch off, we were able to recover most of the data and realign it to the correct date and time. For one of the respective participants, we were able to recover all relevant data. For another one, the last day of data acquisition as well as the last 30 minutes from the second-to-last day are missing. For the last participant, we could only recover the last four days of data acquisition. For the day with the missing data in the 30 minutes prior to bedtime, we wanted to substitute the missing lux and UV light data with the averaged values of the same participant in the same timeframe. This procedure has been used by Franklin (2020) for data excluded as invalid. However, there was only one day of data in which the participant had still been awake during said timeframe. Thus, we estimated lux and UV light data for the missing 30 minutes with the mean data of this day's respective timeframe. Overall, we thus generated analyzable data for the complete data acquisition period from four participants, as well as data from six and four consecutive days for one participant each.

3.3.2.7.4.3. Pre-Processing

From this data, we excluded times with a lux measurement of zero for ≥ 15 minutes during daytime from analysis as we assumed that the device had been concealed or not worn during this time, hence rendering the data invalid (Franklin, 2020; Read et al., 2014, 2015; Ulaganathan et al., 2019b). We defined daytime as the time between sunrise and sunset during which the participant was awake, thus combining approaches from other investigations (Alvarez & Wildsoet, 2013; Bhandari et al., 2022; Landis et al., 2018). We initially planned on performing a similar exclusion procedure for motion data (i.e., excluding times without movement for ≥ 15 minutes as invalid), as this procedure has been described for both lux and activity data before (Franklin, 2020; Read et al., 2014, 2015; Ulaganathan et al., 2019b). For this, we planned on using the "motion" value, indicating movement if the sum of the gyroscope values (gx, gy, gz) was equal to or above our movement threshold of 2000 (see chapter 3.3.2.2) and no movement if that was the case. However, we found that when using said criterion, a large amount of time would be excluded, and manual data inspection revealed that there seemed to have been movement during a number of the respective times, despite the "motion" value indicating otherwise. Thus, while this exclusion procedure based on motion data is theoretically possible with data from our devices, we did not do it here, as we presumed that we had set the motion threshold too high for this procedure to only (or primarily) exclude invalid data. We therefore only excluded data with a lux measurement of zero for ≥ 15 minutes as invalid. Some of this data could be replaced based on the study diaries, if the overall day was considered valid (see below).

We then used the study diaries to assess participant-indicated times of device non-wear or concealment (non-wear periods) for ≥ 15 minutes. We manually checked the data around the indicated non-wear periods, and if it showed that the device had (most likely) been concealed or not worn for a longer period than indicated in the diary, we expanded the respective non-wear period. For this, we used the abovementioned "motion" value. Despite our finding that it was most likely not triggered in case of little movement (e.g., when working at a desk) and our subsequent decision not to exclude times during which the threshold had not been reached for ≥ 15 minutes, stronger movements such as putting the device back on after non-wear would certainly be enough to reach the threshold. Thus, if the participant had indicated that the device had been placed somewhere and not moved during the non-wear period, we primarily used the "motion" value to identify the correct start and end times of the non-wear period – since we assumed that the device would need to be moved considerably when removing it or putting it back on. On the other hand, if the participant had indicated that the device had been carried around in a bag during the non-wear period, we primarily used lux data to assess the non-wear periods. Specifically, we expanded the participant-indicated period to include adjacent times with a constant measurement of 0 lux, if there were any. While we did expand non-wear periods based on manual data assessment as just described, we did not shorten them if the data indicated that a participant might have protocolled a longer non-wear period than there had actually been. We did not do this, as the presence of movement (within a protocolled non-wear period with the device placed somewhere) or of more than 0 lux (within a protocolled non-wear period with the device in a bag) does not necessarily imply that the device had actually been worn – while on the other hand, the absence of movement or lux measurement does imply that the device had not been worn or exposed to light. Similarly, we manually assessed the data around the participant-indicated timepoints of getting up and going to bed and expanded participants' sleeping time – i.e., the time between said timepoints – if voltage, "motion" value and sometimes also lux value showed that the device had not been worn for a longer than indicated time. Specifically, we assessed if the voltage values indicated that the device had still (already) been connected to the charger after (prior to) the participant-indicated time of getting up (going to bed), and if the first (last) movement of the device was after (before) the indicated time of getting up (going to bed). In these cases, we expanded the participant's sleeping time accordingly. Usually, the voltage and "motion" values coincided very well to pinpoint exactly when the device had been removed from or connected to the charger. Over all participants, there were two cases with unclear results of this manual data assessment, and we did not expand the sleeping time in these cases – which, however, only accumulate to 7 minutes. We again chose a conservative approach and did not shorten participants' sleeping time if the data indicated that it might have been shorter than protocolled as we could not be sure if changes in voltage, "motion" or lux values were actually indicative device wear.

For data analysis, we only included days with ≥ 90% of valid daytime data (Read et al., 2014, 2015). Thereby, we defined a day as the time from the participant getting up in the morning to going to bed at night – if the participant went to bed after midnight, the time after midnight would be counted for the previous day. For included days, if possible, we replaced data from participant-indicated non-wear periods. Similar to Read et al. (2014, 2015), we used the average value of the 5 minutes prior to and after the non-wear period if consistent with the diary regarding indoor or outdoor location. In case the non-wear period occurred directly after (prior to) the participant getting up (going to bed), we only used average data of the 5 minutes after (prior to) the non-wear period. We used the ideal lux indoor-outdoor cut-off determined in the TM to check for consistency. In case of inconsistency, the data was removed (Ulaganathan et al., 2019b).

3.3.2.7.4.4. Typical Analyses in the Study of Light-Myopia Associations

We then conducted and assessed typical analyses in the study of light-myopia associations. Firstly, we calculated the time spent indoors versus outdoors during daytime based on the lux and UV light cut-off derived from the TM as well as the 1,000 lux cut-off, with outdoors being operationalized as lux/UV light values equal to or above the cut-off. Time spent indoors versus outdoors was calculated over all participants as well as per individual participant. Furthermore, we plotted lux and UV light data over time for exemplary days and participants.

3.3.3. Results and Discussion

Importantly, we conducted this study to assess the feasibility of our devices for data acquisition, pre-processing, and some typical light data analyses regarding myopia research. The data was, however, not used for an actual evaluation of light-myopia associations. Thus, some procedures may seem unnecessary, since the respective data was not always used further. Yet again, the goal of this investigation was to assess the feasibility of the device for myopia research, including data analysis procedures, which is why we performed the respective steps nonetheless.

3.3.3.1. Device Comparison Measurements

Table 3.7 presents means and standard deviations for all DCM conditions and devices for both lux and UV light measurements. The DCM revealed an issue with the UV sensor of device 2: In the absence of light, UV light measurements were logged, while the opposite was true whenever the device was exposed to light. This can be seen in Figure 3.10 and Figure 3.11, displaying lux and UV light readings of all devices for the static and moving DCM on a

logarithmic scale, respectively. The same data is presented with linear scaling in Supplementary Figure E1 and Supplementary Figure E2. We thus removed device 2 from further measurements.

Table 3.7

Lux and UV Light Mean (Standard Deviation) Values of the Device Comparison Measurements

condition	measure	device 1	device 2	device 3	device 4	device 5
indoors – with light	lux	365.1 (59.6)	411.6 (71.0)	427.5 (75.2)	437.0 (76.7)	450.3 (78.5)
	UV light (nA)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
indoors – without light	lux	346.0 (52.9)	394.3 (60.3)	419.4 (55.8)	407.1 (56.4)	411.8 (52.4)
	UV light (nA)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
outdoors – balcony	lux	206.2 (4.5)	217.2 (4.9)	214.5 (3.9)	220.2 (4.3)	221.1 (4.4)
	UV light (nA)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
outdoors – free sky	lux	11,407.6 (178.2)	12,138.5 (170.8)	12,381.1 (200.1)	12,250.5 (211.0)	12,212.2 (207.6)
	UV light (nA)	56.3 (1.3)	0.0 (0.0)	57.9 (1.3)	51.6 (1.5)	55.9 (1.3)
Moving	lux	3847.5 (1687.9)	4342.9 (1961.6)	4525.0 (2017.2)	4501.1 (1873.8)	4463.8 (1919.2)
	UV light (nA)	13.7 (8.1)	0.0 (0.0)	15.1 (8.0)	10.7 (7.2)	14.1 (7.5)

Note. The UV light data from devices 2 and 4 is marked gray due to (suspected) faulty measurements.

Device 4 demonstrated problems with the UV light measurement as well – in pilot tests, we had observed large and frequent fluctuations between low and high UV light output in situations where it should in fact be constant (and was for the other devices). These fluctuations were not as frequent during DCM, but device 4 still had lower UV light measurements than devices 1, 3 and 5 (see Table 3.7), and its UV light output dropped to zero multiple times during the moving DCM when that of the other devices did not (see Figure 3.11). Especially as we did not know whether the latter was simply due to device 4 measuring

lower UV light than the other devices in general and whether its previously seen UV light measurement fluctuations would reoccur, we removed device 4 from further measurements as well.

Also, it is apparent in Table 3.7 (and Figure 3.10 for the indoor conditions as well as Supplementary Figure E1 for the outdoors – free sky condition) that lux measurements from device 1 are slightly lower than those of the other devices. However, there was some variability between all devices' lux measurements and no further or mechanical problems with device 1 were identified. As one aim of this study was to investigate usability and comparability of (functioning) custom prototypes, we did not remove device 1 from the next parts of the study and chose devices 1, 3 and 5 for further use.

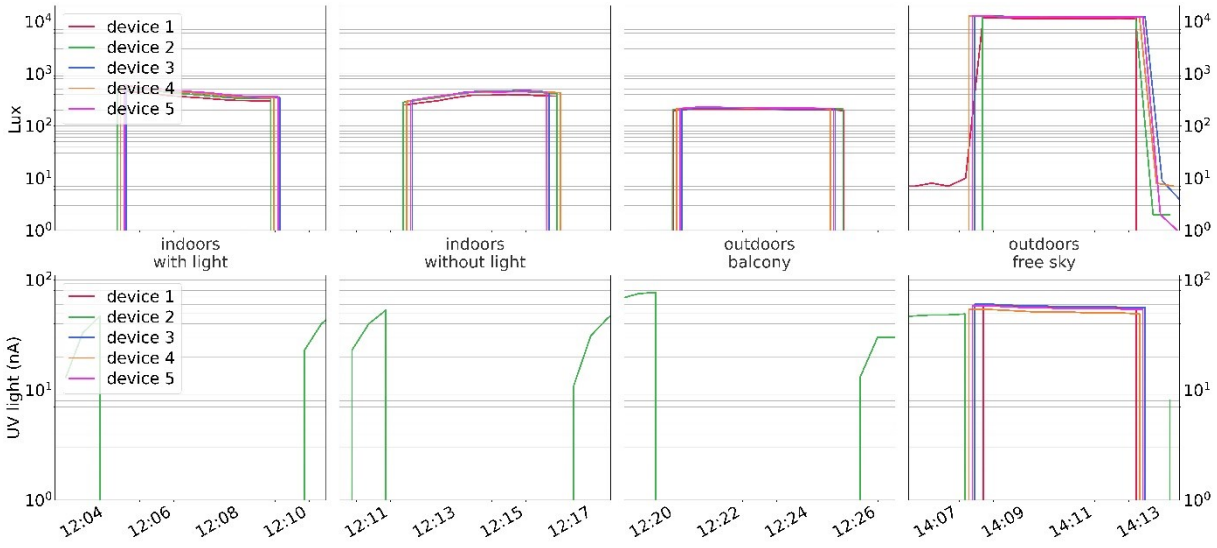


Figure 3.10. Lux and UV light data from the static device comparison measures plotted over time on a logarithmic scale. The devices were covered with a black cloth prior and after each measurement. In the outdoors – free sky condition, it is visible in the plot that some devices measured some light despite being covered. Beginning and end of each measurement are still easily recognizable for all conditions. In the UV light measurements, the malfunction of device 2 is evident, as it always logged UV light measurement when the devices were covered, but not when they were not. Furthermore, a slight offset between the devices with regard to start and end of measurements can be seen in all conditions. This is due to the fact that their measurement times are not perfectly aligned. Due to the 30 seconds measuring interval, a between-device offset of up to 30 seconds is possible. Lastly, the time intervals between the individual plots (i.e., measurement conditions) vary, and there is a slight overlap between the first two plots since the respective measurements were taken in close temporal proximity.

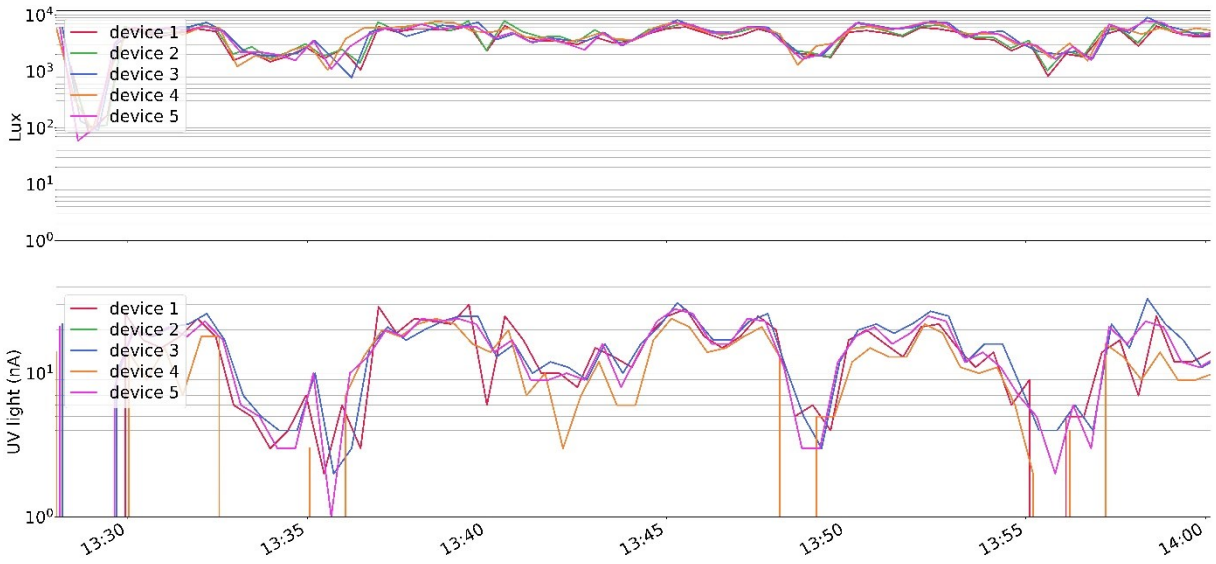


Figure 3.11. Lux and UV light data from the moving device comparison measurement plotted over time on a logarithmic scale. In the UV light measurements, the malfunction of device 2 is evident in that it did not measure UV light at all. The (potential) malfunction of device 4 is also evident, as its UV light measurements dropped to zero multiple times when those of the other devices did not.

We calculated the ICCs for these three included devices. They were 1.00 for the static and 0.76 for the moving DCM for lux, and 1.00 and 0.77 for the static and moving DCM for UV light, respectively. According to rules of thumb suggested by Koo and Li (2016), the ICCs thereby indicate good reliability in the moving DCM and excellent reliability in the static DCM for both measurements.

Wen et al. (2021) report a similarly high ICC (1.00) for illuminance for static measurements with Clouclip, while Read et al. (2014) report a higher ICC (0.99) for moving measurements with Actiwatch 2 devices. Ostrin (2017) also conducted measurements similar to our DCM, but does not report ICC values. However, neither Wen et al. (2021) nor Read et al. (2014) indicate the ICC model used, so we cannot with certainty assume comparability between our and their results. As described in Data Analysis, there are multiple ICC models. Their selection involves making assumptions, and results and interpretations vary between ICC models applied to the same data (Koo & Li, 2016). For example, had we chosen multiple measurements instead of single measurement – on the basis of being interested in the general agreement between devices instead of specific measurements of individual devices –, our moving DCM would have resulted in ICCs of 0.90 and 0.91 for lux and UV light, respectively. Likewise, consistency models, allowing for systematic differences between ratings (i.e., devices), yield higher ICCs than absolute agreement models (Koo & Li, 2016). Had we chosen a consistency instead of an absolute agreement assessment, the moving DCM ICCs would have been 0.92 (lux) and 0.91 (UV light).

Overall, our data shows good reliability for the moving and excellent reliability for the static DCM for both lux and UV light. Regarding lux, the static DCM results are similar to measurements with Clouclip (Wen et al., 2021). The moving DCM results indicate reduced reliability compared to Actiwatch 2 measurements (Read et al., 2014) – though due to lack of knowledge regarding the calculation of the latter, we do not know the magnitude of the difference. Lastly, it is important to consider the presence of methodological differences between the studies, e.g. with regard to the number of devices or exact measurement protocol, further restricting comparability.

3.3.3.2. Category Measurements

Means and standard deviations for all CM are presented in Table 3.8 and Table 3.9 for lux and UV light, respectively. A large between-device variability for the same categories is readily apparent for both lux and UV light data, which presumably largely depends on the circumstances of data acquisition. The slight deviation in lux measurements that was detected in the DCM for device 1 is likely not the (main) reason for the CM variability: Device 1 often displays higher mean values than the other devices, and there is similar variability in the UV light data.

Table 3.8

Lux Mean (Standard Deviation) Values of the Category Measurements

	device 1		device 3		device 5	
category	**sunny**	**cloudy**	**sunny**	**cloudy**	**sunny**	**cloudy**
outdoors – free	54,612.0 (0.0)	4,963.7 (2,484.8)	4,684.4 (364.0)	12,323.9 (4,130.1)	11,702.0 (12,787.4)	12,838.1 (4,538.8)
outdoors – covered	5,292.5 (360.4)	975.8 (62.2)	2,441.8 (165.3)	507.5 (93.1)	709.7 (7,504.0)	2,219.1 (1,436.6)
indoors – open window	34,806.0 (9848.0)	7,710.9 (668.6)	1,152.4 (174.6)	1,020.6 (141.5)	52,730.8 (7,504.0)	5,367.1 (884.3)
indoors – closed window	24,037.4 (9,499.7)	5,084.9 (295.8)	3,256.8 (372.4)	903.8 (417.3)	53,577.3 (1,490.9)	1,274.6 (233.6)
indoors – towards window	878.5 (280.4)	138.9 (13.6)	240.4 (337.1)	429.1 (92.4)	43,393.4 (7,136.2)	333.1 (155.4)
indoors – regardless of window	1,669.5 (1,508.2)	60.05 (102.9)	491.2 (51.8)	246.6 (255.8)	626.2 (727.8)	381.0 (456.5)
indoors – away from window	167.7 (15.4)	131.6 (17.5)	19.1 (6.5)	26.5 (2.8)	85.5 (21.1)	79.8 (20.3)
indoors – no window	7.0 (6.3)	1.7 (0.9)	2.8 (1.3)	9.7 (2.0)	15.2 (10.3)	1.8 (1.5)
indoors – artificial light	14.0 (0.0)		2.1 (1.8)		26.6 (17.6)	

Note. "indoors – artificial light" was only acquired once, regardless of weather conditions, as the measurement was completed after sunset and with artificial illumination.

Table 3.9

UV Light Mean (Standard Deviation) Values of the Category Measurements

	device 1		device 2		device 3	
category	**sunny**	**cloudy**	**sunny**	**cloudy**	**sunny**	**cloudy**
outdoors – free	318.8 (14.1)	21.2 (11.9)	31.7 (0.8)	71.4 (17.9)	16.6 (7.0)	51.2 (15.1)
outdoors – covered	39.5 (3.3)	1.6 (0.5)	14.5 (0.7)	1.9 (0.6)	1.2 (1.7)	6.3 (5.7)
indoors – open window	112.2 (48.6)	35.9 (4.2)	1.55 (0.5)	2.0 (0.7)	220.8 (34.1)	19.7 (2.9)
indoors – closed window	20.4 (17.4)	5.3 (0.4)	5.5 (1.4)	0.4 (0.5)	76.2 (2.8)	1.2 (0.7)
indoors – towards window	0.0 (0.0)	0.0 (0.0)	0.2 (0.5)	0.0 (0.0)	36.5 (14.0)	0.0 (0.0)
indoors – regardless of window	0.9 (1.8)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.1 (0.4)	0.1 (0.2)
indoors – away from window	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
indoors – no window	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
indoors – artificial light	0.0 (0.0)		0.0 (0.0)		0.0 (0.0)	

Note. UV light values are given in nA. "indoors – artificial light" was only acquired once, regardless of weather conditions, as the measurement was completed after sunset and with artificial illumination.

Furthermore, the data shows the impossibility of correctly classifying indoors versus outdoors with one cut-off value, due to large overlaps between indoor and outdoor measurements. Especially the categories "indoors – open window" and "indoors – closed window", where the experimenters were directly oriented towards a window, display lux – and UV light – values similar to those of the outdoor rather than the other indoor categories. Given that standing directly in front of a window, especially if it is open, generally resembles being outside more than being inside regarding aspects like light exposure and viewing behavior, this result is not necessarily surprising. In fact, one would probably want to consider such situations as "outdoors" in a field data acquisition due to their characteristics. We thus did not consider both these categories in our assessment regarding an indoor-outdoor cut-off value. Device 5 also displays extremely high lux and UV light mean values for the "indoors – towards window" measurements as compared to the other devices. As reflected upon

earlier, this is likely due to different circumstances of data acquisition, e.g. the experimenter being directly in the sun or it being an extremely bright, sunny day. Yet, we kept considering this category as indoors, because it does not possess the same outdoor-like characteristics as "indoors – open window" and "indoors – closed window", and similar situations may happen in a field study as well.

However, there are also overlaps between indoor and outdoor measurements of other categories, especially for lux. This has been reported from comparable measurements before (Dharani et al., 2012) and can also be seen in Figure 3.12, displaying the number of lux measurements per lux values for the CM over all three devices and categories except "indoors – open window" and "indoors – closed window" and "indoors – artificial light" – which was also excluded to avoid overloading the figure panels, as it was acquired after sunset and the measurements were thus uniformly low. The extremely high lux values (between ca. 30,000 lux and 55,000 lux) that can be seen in the plot "indoor categories (all measurements)" all stem from the "indoors – towards window" measurements already discussed with regard to Table 3.8. But even apart from these extreme cases, many overlaps between indoor and outdoor lux measurements are clearly visible, demonstrating the difficulty of choosing one lux cut-off value for indoor-outdoor discrimination. Visually, good lux cut-off values cannot be easily determined due to said overlaps, especially < 2,000 lux. As already described, we will arithmetically determine a lux (and UV) cut-off value for these devices for the TM data via ROC curve analyses (see chapter 3.3.3.3).

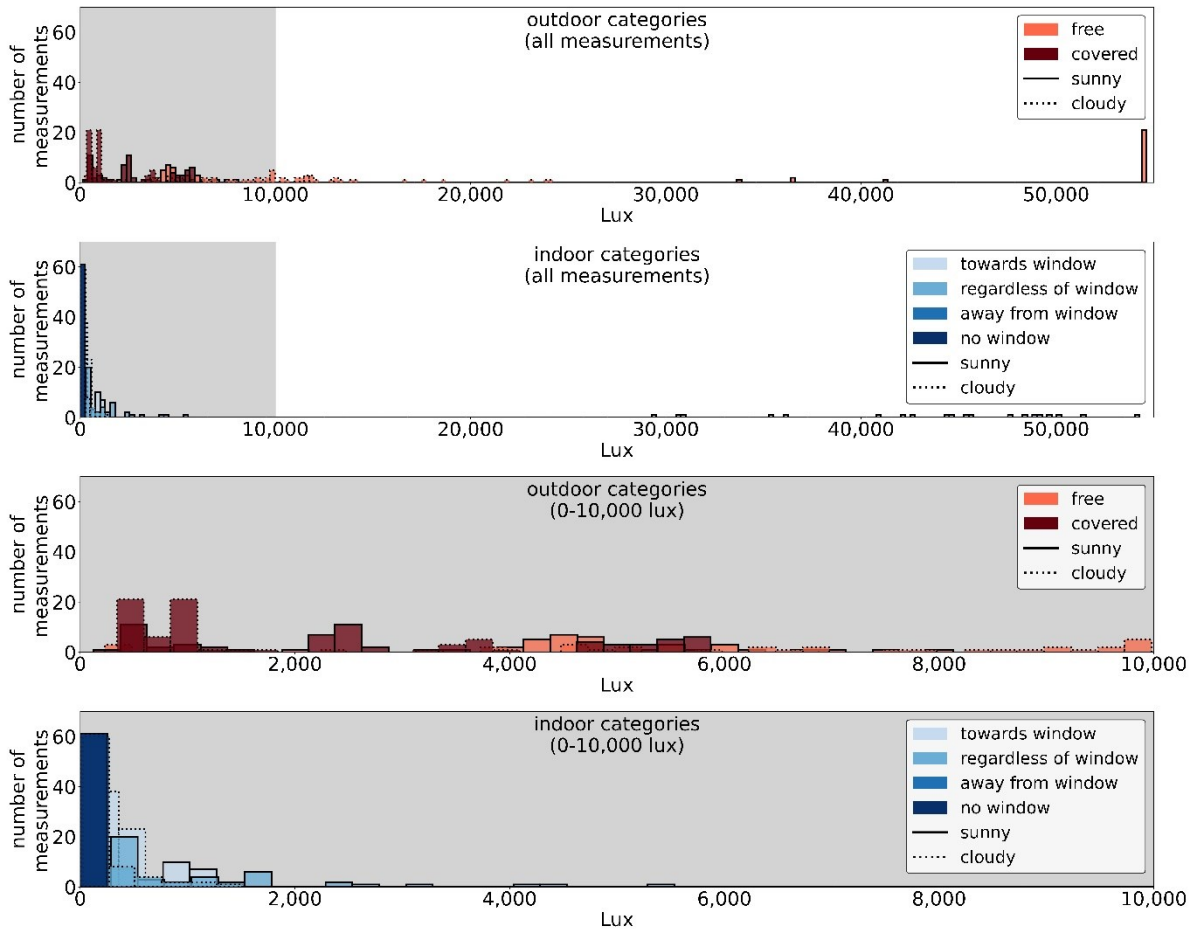


Figure 3.12. Number of lux measurements in bins of 250 lux over all devices per category from the category measurements. Indoor and outdoor categories are shown separately. All data from daytime measurements is shown, except for the categories "indoors – open window" and "indoors – closed window". The upper plots show the complete range of measurements, while the lower plots show the data up to 10,000 lux, as indicated by the gray background.

Figure 3.13 presents the number of measurements per UV light value for the CM. Again, there is some overlap between indoors and outdoors, but considerably less so than for lux. Thus, the indoor-outdoor distinction using a single cut-off value seems to be more clear-cut with UV light than lux in our data. Specifically, in the overwhelming majority of indoor measurements, we measured no UV light at all, while this was the case for almost all outdoor measurements. This is also well visible in Table 3.9 – again, except for the already discussed categories "indoor – open window" and "indoor – closed window" and the partly extremely high UV light values for "indoors – towards window", which also represent the highest UV light values measured indoors in Figure 3.13.

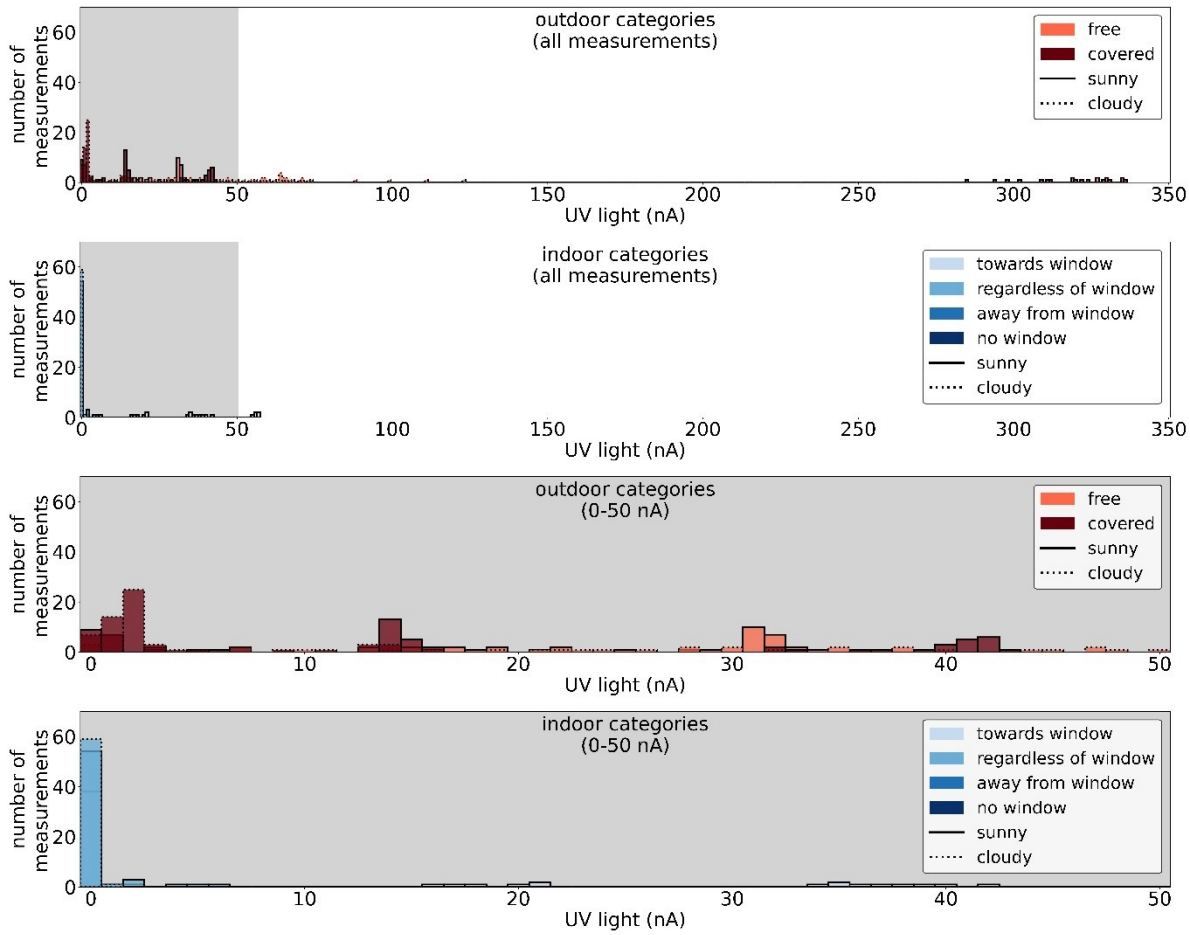


Figure 3.13. Number of UV light measurements over all devices per category from the category measurements. Indoor and outdoor categories are shown separately. All data from daytime measurements is shown, except for the categories "indoors – open window" and "indoors – closed window". The upper plots show the complete range of measurements, while the lower plots show the data up to 50 nA, as indicated by the gray background.

3.3.3.3. Test Measurements

Overall, we had to remove 58 minutes (one instance) of device non-wear. We also removed 3 hours and 18 minutes of data that were within the 2-minute timeframe of a location transition, and 2 hours and 14 minutes of data due to an unclear location with regard to indoors versus outdoors. This led to a total of 37 hours and 54 minutes of included data from all three devices.

When maximizing the sum of sensitivity (percentage of actual outdoor time correctly identified by the respective cut-off value) and specificity (percentage of actual indoor time correctly identified by the respective cut-off value), ROC curve analyses revealed 850 lux as the best lux cut-off for indoor-outdoor discrimination. For 850 lux, the sensitivity was 90.2% and the specificity 89.2%. Interestingly, these sensitivity and specificity values are

comparable to those of commercially available devices in Study 5, showing that our device prototypes generally performed comparably well in discriminating indoors from outdoors with via a lux cut-off. Unlike what we found for some devices in Study 5, the commonly used 1,000 lux cut-off yielded an almost similarly good sensitivity (88.7%) and specificity (90.5%) in the TM.

ROC curve analysis for UV light readings yielded 2 nA as the best indoor-outdoor cut-off, exhibiting a sensitivity of 91.7% and a specificity of 99.7%. Thus, as already speculated from the visual assessment of the CM results (Figure 3.13), the UV light cut-off performed better than the lux cut-off in indoor-outdoor discrimination. If one aims at discriminating indoor from outdoor exposure from wearable device data with a single value, it may – depending on the device and data acquisition circumstances – thus be helpful to consider using UV light rather than lux data. In Study 5, we also found UV light to perform well in indoor-outdoor discrimination for the one device that measured it (Vivior Monitor), although in this case, the best lux cut-off performed slightly better than the best UV light cut-off.

3.3.3.4. Field Test

3.3.3.4.1. Participant Questionnaire Data

According to their self-report in the post-questionnaire, none of the six participants had changed their daily routine due to the device. When asked about how much they had noticed the device (from 1 – "I did not notice it in my daily routine" to 5 – "I did notice it in my daily routine and it bothered me a lot"), two participants indicated a 2 ("I did notice it in my daily routine but it did not bother me"), and the other four indicated a 3 ("I did notice it in my daily routine and it bothered me a little"). Thus, the majority of participants found the device to be a little bit disruptive, but none more than that. Furthermore, all participants stated that there had been no situation with the device that they had been asked to avoid (e.g., being underwater).

With regard to the devices, participants indicated the following: Two participants stated that they had almost forgotten they were wearing the device in many situations as it was not really disruptive. One participant specified that especially when wearing the device outside over a jacket, they did not notice it. On the other hand, one participant indicated that the device can in fact be disruptive in daily life activities, and another one described that the device had been least disruptive outdoors, but sometimes annoying indoors, and that its disruptiveness had very much depended on the situation. Regarding wearing comfort and complications, one participant described difficulties with wearing the device over a jacket because using the extension had been complicated. They suggested a generally longer band. Another participant stressed the importance of using the extension with the currently used

case as it would not have fit over a jacket otherwise. One participant stated that wearing the device directly on the skin (in hot weather) had been unpleasant, especially for longer periods of time. There were also some comments on the device's wearing position. For example, two participants stated that the device had sometimes shifted on the arm (e.g., sliding to the side or downwards), and that it might be helpful to use an elastic band or another way of fixation. Furthermore, noticeability was mentioned twice, suggesting a smaller and less noticeable device for the future, including a darker color. One participant specified having felt watched when wearing the device. They elaborated that this might have been less problematic during the Covid-19 pandemic due to being among others less often, but that participants would probably take the device off more often in other circumstances due to its noticeability. Lastly, some comments were made with regard to device handling. One participant explained that they had often needed to be careful to not accidentally cover the sensors, e.g. when lying on the couch. It was also mentioned that an outside charging indicator would be helpful as participants could not see whether the charging had been successful. One participant described that the device's case had been somewhat damaged because of the frequent use. For example, the Velcro band at the back had almost been detached, the front foil had been somewhat discolored, and they would have preferred to be able to wash the case after wearing it on bare skin. Interestingly, participants in another study made similar comments regarding a device worn the same way as ours, e.g. criticizing the armband as well as both wearing the device around the outermost layer of clothing on cold days and when only wearing t-shirts (Phan, 2022).

We had asked participants to estimate the comparability of their current daily life to their daily life prior to the Covid-19 pandemic on a scale from 0 (completely different) to 100 (exactly the same). Participants' estimates ranged from 20 to 73, with a mean of 41.3. As has also been mentioned by a participant in the open questions (see above), this indicates limitations in the comparability of data acquisition during the pandemic versus at other times. The situation regarding the Covid-19 pandemic demonstrates the restricted comparability to non-pandemic times as well: Data acquisition took part amidst a lockdown, including varying restrictions and recommendations with regard to e.g. social gatherings, the entering of stores and restaurants, remote work and university classes, and nightly curfews. It is obvious that for most people, measures such as these severely impact daily life – for example, time spent in social situations, during which they might feel self-conscious about the device, is likely decreased compared to non-pandemic times. All this should be kept in mind in evaluating the present data, e.g. regarding non-wear of the device or their usual daily activities.

3.3.3.4.2. Pre-Processing and Data Quality

As described in chapter 3.3.2.7, 4 days of field test data overall were missing due to device failure. Furthermore, 30 minutes that were also missing were replaced by data from the same time and location at another day of the same participant and thus kept in.

From their self-report, participants mostly removed the devices when they could not be worn, e.g. while showering. From the 30 days with available data, 32 hours and 20 minutes were missing due to self-reported non-wear periods at 29 instances, including both day- and nighttime. 15 hours and 25 minutes (23 instances) of this were missing while the participants were indoors, and 16 hours and 55 minutes (six instances) while they were outdoors. Reasons for indoor non-wear were mostly body care and/or showering (20 instances). Outdoor non-wear usually occurred because the device bothered the participants, especially in social situations (four instances). Most missing data due to non-wear – 18 hours and 1 minute – stem from one participant, who repeatedly removed the device for longer periods outdoors. Specifically, said participant spent 16 hours and 24 minutes of non-wear time outdoors, and was responsible for five of the six instances of outdoor device non-wear. Furthermore, 36 hours and 51 minutes of overall data was invalid due to periods of 0 lux measured for ≥ 15 minutes during daytime.

Nine of the 30 available days were removed because of < 90% valid daytime data, leaving 21 days for analysis. The latter encompassed 18 self-reported non-wear periods (10 hours and 5 minutes), of which we were able to replace data for 15 periods (8 hours and 11 minutes) as described in chapter 3.3.2.7. This accumulates to 2.3% of the total included data being replaced. Approximately the same percentage of data was replaced in Read et al. (2014). However, the aforementioned absence of data exclusion due to missing motion should be noted here. As this exclusion procedure was performed by Read et al. (2014) in addition to the lux-based exclusion that we also used, it is likely that the amount of excluded data in our study would surpass theirs, had we also included this procedure. The remaining self-reported non-wear data were excluded from analysis, as were the times identified as invalid data due to zero lux during daytime that were not covered with a self-reported non-wear period, accumulating to 4 hours and 3 minutes of data excluded from analysis for the included days.

The amount of days removed for too much invalid data is rather high in comparison to investigations of light-myopia associations (see Table 3.2 in Study 4 – Hönekopp & Weigelt, 2023). Importantly, 4 of the 9 days that were removed as invalid stem from the aforementioned participant, who often removed the device for longer periods of time. When analyzing such data with regard to content – e.g., to investigate light-myopia associations –, it would most likely be advisable to exclude participants with such unreliable wearing behavior (as well as those with several days of technical device failure) from analysis. In fact,

some investigations do include a criterion for excluding complete data sets, usually by setting a minimum number of valid days needed to be included for analysis (Bhandari et al., 2022; Franklin, 2020; Z. Liu et al., 2021; Wen et al., 2020). We did not use a respective criterion, because ours is a feasibility study and not an investigation in which the content of the measured data is of particular relevance.

3.3.3.4.3. Typical Analyses in the Study of Light-Myopia Associations

For the included days, the overall outdoors (indoors) time during daytime was 81 hours and 11 minutes (263 hours and 3 minutes) for the TM-derived ideal lux cut-off (850 lux). We also calculated outdoor (indoor) time for the 1,000 lux cut-off as well as the ideal UV light cut-off (2 nA), which was 76 hours and 20 minutes (267 hours and 54 minutes) and 69 hours and 56 minutes (274 hours and 18 minutes), respectively. The proportion of time spent indoors versus outdoors according to the three cut-offs is visualized in Figure 3.14 – showing that the differences in indoor-outdoor classification are very small between them.

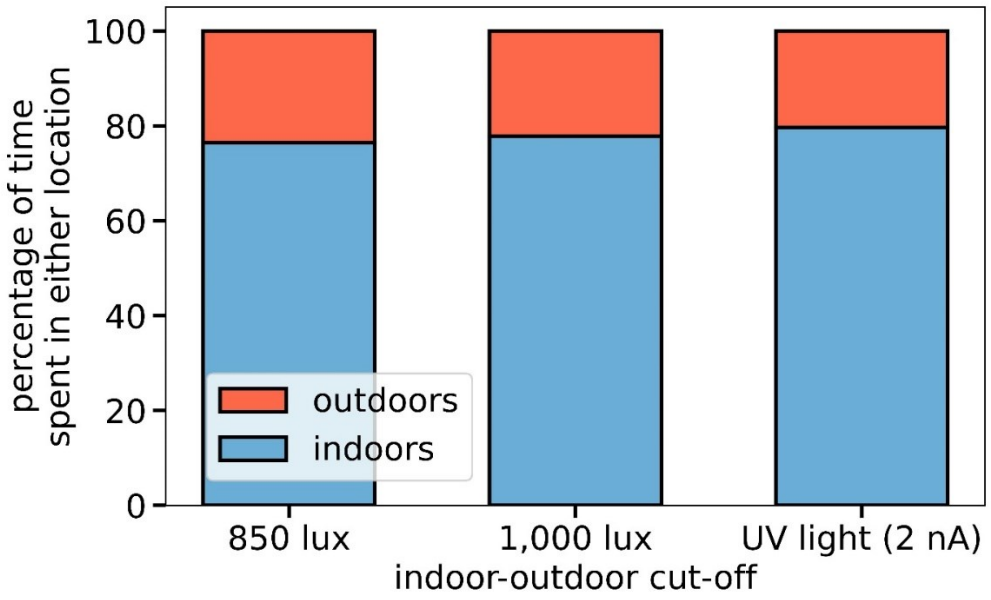


Figure 3.14. Percentage of time spent indoors and outdoors according to the cut-offs used.

Table 3.10 presents the respective data per individual participant. The successful calculation of time spent indoors versus outdoors with several cut-off values demonstrates our prototype's ability to produce data on time spent in different light levels that can be used for further analyses on light-myopia associations. Furthermore, large between-participant differences in the time spent in- and outdoors are clearly visible, but will not be analyzed further at this point.

Table 3.10

Time Spent Indoors and Outdoors per Participant According to Different Cut-offs

		participant					
cut-off	**location**	**1**	**2**	**3**	**4**	**5**	**6**
850 lux	outdoors	31:47 (44%)	01:43 (5%)	06:41 (9%)	22:04 (26%)	07:01 (25%)	11:53 (23%)
	Indoors	40:18 (56%)	30:22 (95%)	68:14 (91%)	62:21 (74%)	21:29 (75%)	40:19 (77%)
1,000 lux	outdoors	30:32 (42%)	01:30 (5%)	06:15 (8%)	20:35 (24%)	06:37 (23%)	10:50 (21%)
	Indoors	41:33 (58%)	30:35 (95%)	68:40 (92%)	63:50 (76%)	21:53 (77%)	41:22 (79%)
UV light (2 nA)	outdoors	28:16 (39%)	01:25 (4%)	05:23 (7%)	19:20 (23%)	06:26 (23%)	09:05 (17%)
	Indoors	43:49 (61%)	30:40 (96%)	69:32 (93%)	65:05 (77%)	22:04 (77%)	43:07 (83%)

Note. Time is given in hours:minutes (%). Importantly, the absolute times are not comparable between participants since differing numbers of days were included in the analysis.

The data show very similar calculated time spent indoors and outdoors between the 1,000 lux and the 850 lux cut-off, with only 1% fewer outdoor time classified with the former. Considering the small difference in their sensitivity and specificity in the TM, this is not unexpected. Thus, our analyses suggest that for our prototype and the given data acquisition environment, the 1,000 lux cut-off is usable as well. Interestingly, comparable results were found by Alvarez and Wildsoet (2013) using the HOBO Pendant UA-002-64, who had originally determined 882 lux as the best indoor-outdoor cut-off for their data from pre-measurements. However, the results did not differ from those with the 1,000 lux cut-off, and they thus used the latter in their analyses for comparability with other research (Alvarez & Wildsoet, 2013). In our study, the UV light cut-off results also do not differ much from those of the lux cut-offs: The former classifies 2% (3%) fewer outdoor time than the 1,000 (850) lux cut-off. In the TM, the UV light cut-off had a higher sensitivity and specificity than both lux cut-offs, and the 850 lux cut-off had a slightly higher sum of sensitivity and specificity than the 1,000 lux cut-off. However, both the aforementioned numbers and Table 3.10 demonstrate that in the field test, the UV light cut-off differs slightly more from the 850 lux than the 1,000 lux one – potentially indicating some environmental variation, e.g., regarding lighting conditions, between the TM and the field test.

Finally, Figure 3.15 visualizes one day of lux and UV light measurements for two different participants. Among others, the figure shows which timeframes would be classified as indoor and outdoor with the considered cut-off values, which are also plotted. The interpretation of the data with regard to the plotted cut-off lines is thoroughly described in Figure 3.5 (Study 5).

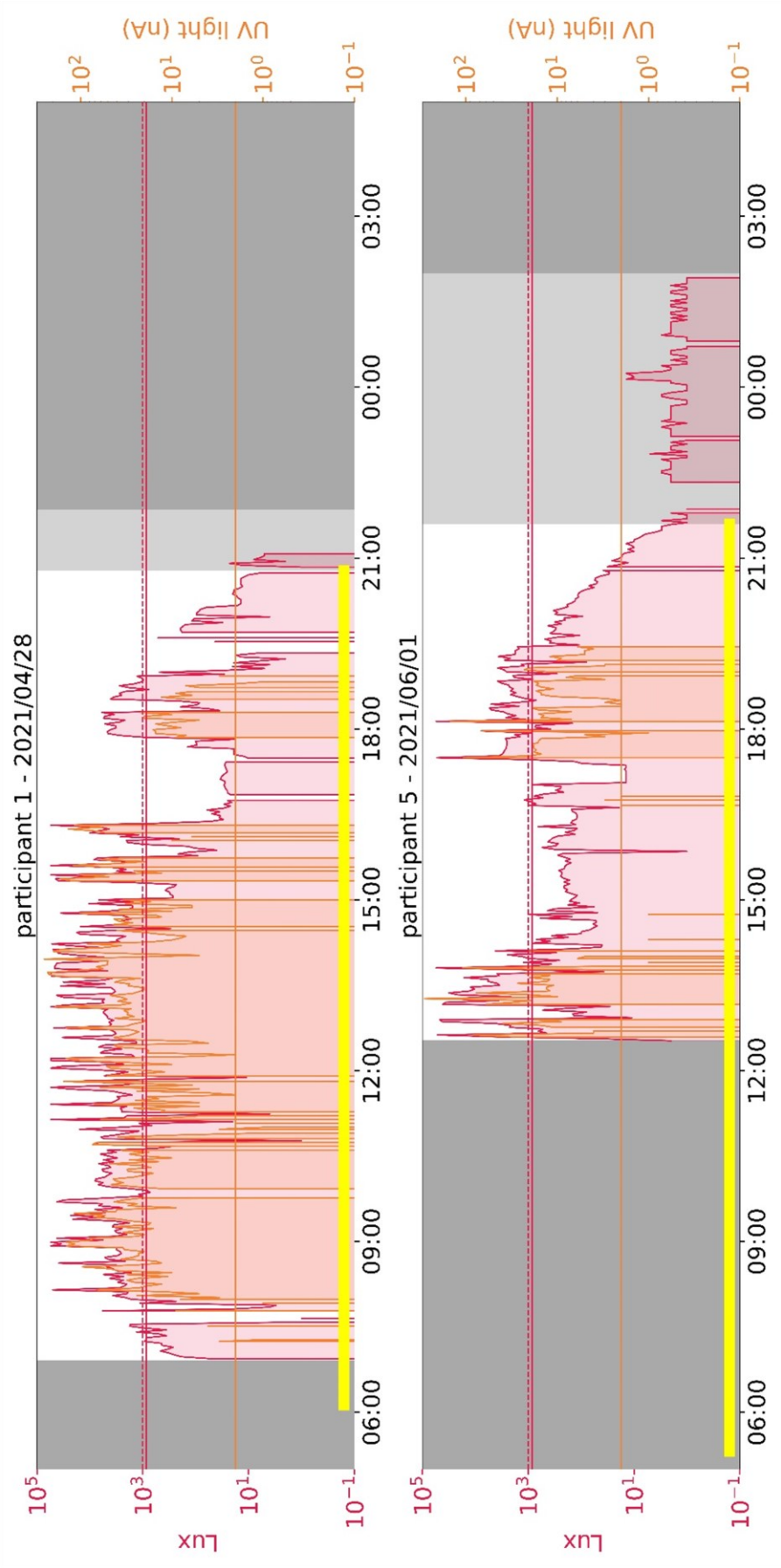


Figure 3.15. Lux and UV light measurements for two exemplary participants and days. Light gray background indicates nighttime – i.e., the time during which the participant was awake prior sunrise or after sunset, though only the latter applies here. Dark gray background indicates participants' sleeping time. The date given for either plot refers to the daytime plotted, with the plots showing 24 hours starting at 5:00h in the morning of the indicated day. To improve visualization, a sampling rate of 2 minutes – i.e., every 4th data point – is plotted. The red horizontal lines indicate the 850 lux (straight) and 1,000 lux (dashed) indoor-outdoor cut-offs. The orange horizontal lines indicate the UV light cut-off (2 nA). The yellow bars indicate the time between sunrise and sunset.

3.3.3.5. Overall Considerations Regarding Device Usability

3.3.3.5.1. Technical Considerations

Firstly, as it is to be expected with prototypes, we encountered some issues regarding mechanical properties and device handling that should be addressed in future versions – encompassing actual technical failures as well as opportunities for improvement. As the development and in-depth description of the hard- and firmware is not the topic of this study, these issues will only be addressed briefly here according to their relevance for data acquisition. For example, in some cases, the UMTS module needed to be exchanged prior data acquisition due to malfunctions. Also, date and time were sometimes not recorded correctly because of this, which entailed problems with timekeeping that are described in chapter 3.3.2.7, and this did not always trigger an SMS to the experimenter phone as intended. Another issue relates to the charging of the device. During field test data acquisition, the devices did not always charge overnight, leading to some missing days of data due to device shut-off. Since the prototypes do not include a charging light visible from the outside and the participants indicated that they had charged their device each night, it is likely that at least some of the missing charging can be attributed to the cable not having been correctly plugged in. This could be overcome with a charging light visible from the outside.

Another opportunity for improvement is to increase the running time of the rechargeable battery, which would especially be relevant in case a participant forgets to charge the device overnight or the charging does not work correctly. However, in theory, the current running time is sufficient for the use case, and some of the problems with regard to the battery might be solved with an outside charging light as described above. Furthermore, the upper lux limit of the ambient light sensor's current (default) mode (54,612 lux) was reached for all participants during data acquisition. For analyses such as indoor-outdoor distinction or of time spent in different light intensities below said limit, this circumstance should not be an issue – it would, however, be problematic when e.g. analyzing cumulative or average lux exposure (e.g., Alvarez & Wildsoet, 2013; Mirhajianmoghadam et al., 2021), which would be underestimated due to the sensor saturation. With regard to the measured light values, it is important to keep in mind that they are not "real", calibrated measures. Depending on the spectral sensitivity of the ambient light sensor, measures may differ from those of a calibrated luxmeter (or photometer), and depending on the overall device, other aspects might also alter how much lux is measured. In our case, this e.g. refers to the lux sensor being placed in a case behind acrylic glass, which likely reduces the lux measurement. As demonstrated by Joyce et al. (2020) for two commercially available devices, one can use a correction factor to recalculate a device's lux measurement to match "real" lux measured by a calibrated photometer. As mentioned earlier, the UV light measurements are currently

given in photocurrent (nA) and would need to be transformed to UV index, if one wants to assess a unit such as this. Furthermore, the UV light sensor is also located in a case behind acrylic glass – which likely, despite its UV permeability, reduced measurements. Thus, to match "real" UV light, a correction factor would be needed here as well.

The prototype has since been revised in students' academic theses, and some of the described issues, for example the outside charging indicator, have already been improved therein. Yet, again, as the device's technical development is not the topic of this investigation, this is not discussed further here. Generally, the prototypes performed adequately and include the required technical specifications to study light-myopia associations.

3.3.3.5.2. Advantages and Disadvantages Compared to Commercially Available Devices

In comparison to commercially available devices, our prototype has some advantages – for example, it includes exactly the sensors we wanted, we are aware of all specifications and can change certain aspects at will, for example the threshold of the "motion" value or the timing and content of as well as triggers for SMS sent to the experimenter phone. Commercially available devices, on the other hand, could be removed from the market – as it happened with the Actiwatch devices at the end of 2023, which are often used in light-myopia research (e.g., Mirhajianmoghadam et al., 2021; Ostrin, 2017; Ostrin et al., 2018; Read et al., 2014, 2015; Ulaganathan et al., 2019b). Furthermore, manufacturers may not report all specifications that might be relevant for the research purposes (Study 4 – Hönekopp & Weigelt, 2023), and may change specifications without notice (Markvart et al., 2015).

On the other hand, self-made devices also have disadvantages compared to commercially available ones. For one, our prototypes were assembled by hand rather than in serial production. Resulting (slight) between-device differences, e.g. in the exact placement of the opening above the sensors, might account for some of the variability that we e.g. encountered in the DCM. Between-device variability in light measurements has, however, also been found in commercially available devices of the same type (Markvart et al., 2015). Furthermore, unlike many commercially available devices, prototypes such as ours do not have external certifications, e.g. regarding the level of water resistance. Furthermore, especially with self-made devices, one needs to ensure that participants are able to handle the device correctly. For example, participants need to be made aware how to safely handle a device powered by a lithium-polymer battery, which likely excludes children as participants when using a device at this development stage. Rechargeable lithium-polymer batteries have the advantage of a high energy density, making them ideal for portable devices. They are thus often used in devices such as mobile phones and have also been used in wearable devices for research purposes before (e.g., R. Williams et al., 2019). Yet, it is important to be aware

how to safely handle devices including such a battery, for example by avoiding overheating or any battery damage.

3.3.3.5.3. Summary of the Findings from Data Acquisition and Analyses

We were able to perform all planned data acquisitions and analyses with our devices. The DCM showed technical problems with two devices that were thus excluded from subsequent measurements. Overall, ICC analyses showed excellent and good reliability for the static and moving conditions, respectively. While for the latter, a higher reliability is reported by Read et al. (2014) for the Actiwatch 2, between-study comparability with regard to the ICC analyses cannot be assumed with certainty. Overall and despite the good and excellent between-device reliability, the DCM showed some variation between the devices' measurements. Thus, actual investigations on light-myopia associations may benefit from further improvement of between-device comparability. Respective calibration procedures have already been suggested for other devices (Markvart et al., 2015).

As expected, there was an overlap between the CM indoor and outdoor conditions for both lux and UV light. This has been reported from comparable measurements with other devices as well (Dharani et al., 2012), and overall demonstrates the limits of using a univariate indoor-outdoor cut-off. The CM also showed that UV light might be a promising candidate for indoor-outdoor classification.

From the TM data, we were able to calculate an ideal indoor-outdoor lux cut-off (850 lux) for our device and the given data acquisition circumstances via ROC curve analysis, which performed well compared to those calculated for commercially available devices in Study 5. At the same time, the commonly used 1,000 lux cut-off also performed well with our device in the given environmental circumstances. As suspected from the CM data, the UV light cut-off showed better sensitivity and specificity than both lux cut-offs.

Lastly, the field test generated valuable information about the device's wearability from participants' assessments. Overall, participants perceived the device as good to wear and not too disturbing. Yet, they also offered some ideas for improvement, for example regarding device noticeability. The latter is especially important since data acquisition took part amid the Covid-19 pandemic, and participants indicated that their daily life differed from pre-pandemic times. Presumably, this includes fewer social contact, and it thus stands to reason that potential issues regarding device noticeability and associated self-consciousness may be larger in non-pandemic times than in the present study. Overall, the chosen pre-processing procedures could be performed with our data. Only the attempted exclusion of data with no movement for ≥ 15 minutes was not performed, as we discovered that the threshold for the "motion" value was apparently chosen inappropriately. Theoretically though, this procedure can be performed with data from our device as well, as it is possible

to change the threshold if one identifies a more suitable one. Data quality was generally satisfactory. We had to remove a rather high amount of days (9 out of 30) due to < 90% valid daytime data, but four of these days stem from the one participant who did not wear the device very reliably. For the included 21 days, we were able to replace the majority of non-wear time (8 hours and 11 minutes), which accumulates to 2.3% of the total included data, and only 4 hours and 3 minutes of data had to be excluded from analysis. The analyses performed to test typical data analysis regarding light-myopia associations – calculating the time spent indoors versus outdoors and data visualization over time – were also successful. The former showed that the three cut-offs tested for this study – the lux (850 lux) and UV light (2 nA) cut-offs calculated as ideal for this study and the commonly used 1,000 lux cut-off – yielded quite similar results. This indicates the suitability of the 1,000 lux cut-off for the data from our device in the study's environmental circumstances. Overall, the field test demonstrated that typical pre-processing and data analysis procedures for investigating light-myopia associations can be performed with data from our device. However, due to the rather low upper lux limit of the ambient like sensor, there are currently restrictions to analyses that we did not perform, such as calculating cumulative lux exposure.

Especially with regard to the field test data, it is important to note that there are many options available for pre-processing and analysis. The methodology differs greatly between studies on light-myopia association, and is not always described in detail (Study 4 – Hönekopp & Weigelt, 2023). For this study, we selected options we deemed representative for the field and also useful for our data and the feasibility assessment of our device. Generally, other options are also possible with our device, such as analyzing the data with another definition of "daytime" or other exclusion criteria. Furthermore, one could also use more than one indicator for indoor-outdoor classification instead of a univariate cut-off. For example, Ye et al. (2019) used lux, UV light and step data for indoor-outdoor discrimination. With our current prototype, one could include lux, UV light and movement data. On the other hand, some specific procedures that can be done with data from other devices cannot be performed with data from ours due to lack of necessary device features. For example, several Actiwatch devices include an off-wrist detector (Study 4 – Hönekopp & Weigelt, 2023), which has in the past been used to monitor participant compliance (Ostrin et al., 2017).

Overall, the various measurements and analyses performed demonstrated the device's feasibility for data acquisition and analyses in relation to light-myopia association research. Many of the issues we encountered could generally be avoided – or, at least, minimized – with future device revisions and testing, for example by reducing its noticeability by changing its color, or identifying a more suitable "motion" value threshold to better include motion data in the analyses.

3.3.3.6. Conclusion and Outlook

Despite the issues and limitations of the device prototype investigated in this study, it is theoretically usable for investigating light-myopia associations.

Overall, the study thus showed that it is indeed possible to develop a wearable device tailored to specific research needs with reasonable effort. Developing and building an own device has certain advantages – for example, one can decide on and is aware of all potentially relevant specifications and is not dependent on the manufacturer, who might not disclose or change device specifications, or take the devices off the market. Furthermore, our prototype has specific advantages for the current use case of research on light-myopia associations, such as the inclusion of UV light measurements, which are presently only included in a few of the devices currently used in said research field (Study 4 – Hönekopp & Weigelt, 2023). However, other devices are better suited or – if possible – changes to the current prototype are needed for some aspects of light-myopia research. This is for example the case for measuring lux above the current upper lux limit or continuous device wear, which would be problematic with our device due to overnight charging and its way of wearing. Some of the issues with the current prototype device could be (and have been) changed with manageable effort – for example, implementing an outside charging indicator or using a different "motion" value threshold. Others, however, would need a significantly larger amount of work and resources, for example considerably reducing the device's size or reducing the amount of necessary battery-related safety instructions. Thus – rather unsurprisingly – to be deployed in the field without (as many) restrictions, our prototype would need some further development.

As the research area has been evolving fast in the last years, there are many commercially available devices which may be used for investigating light-myopia associations (Study 4 – Hönekopp & Weigelt, 2023), and which cover a range of different device characteristics. Thus, as of now and if one is not in need of very specific measurements that none of these devices offer, it would likely be more convenient to use one of these devices instead of developing a custom-made one. Yet, for research areas with less availability of respective devices, it may be a viable option to develop a custom-made (wearable) device for one's research.

3.3.4. Acknowledgements

Thank you to Sean Dalton and Stefan Slooten for conceptualizing, developing and manufacturing the devices (hard- and firmware) as well as troubleshooting throughout data acquisition and creating the Github project. Thank you to Carina Schücker for helping in planning the pre- and post-test assessments. Thank you to Maria Wenning for helping with data acquisition, including field test recruitment and testing. Thank you to Antonia Zabel for helping with data acquisition.

4. General Discussion

In this dissertation, I investigated myopia prevalence rates and associated factors in children and adolescents in Germany as well as methodological aspects regarding the research on light-myopia associations, thereby mainly focusing on the utilized light meters. I will now summarize the general findings of this dissertation and contextualize them with regard to the research objectives outlined in chapter 1.3 and associated topics. Subsequently, I will present avenues and implications for future research as well as practice and public health that arise from the results.

4.1. Summary of Main Findings

Despite myopia currently being a globally relevant topic, up-to-date prevalence rates are scarce for many parts of the world. In Study 1, we thus performed non-cycloplegic refractive measurements in school students in Germany. We found a myopia prevalence of 8.4% in 489 primary school children (grades 3-4, mean age: 9.30±0.78 years) and of 19.5% in 1,032 secondary school children (grades 8-10, mean age: 14.99±1.12 years) as well as a general prevalence increase over the grades and higher myopia prevalence in females than males, with the highest between-gender difference in grade 10. Analyses of refractive error associations generally confirmed said patterns. Furthermore, rates of uncorrected myopia were high, with 51.2% in grades 3-4 and 43.3% in grades 8-10.

Furthermore, we assessed prevalence rates of spectacle ownership and related aspects in 0-17-year-olds via an online questionnaire, thereby also investigating participant recruitment strategies and the usefulness of questionnaires in (myopia) epidemiology research. With regard to the former, we compared five different recruitment strategies in Study 2 and found a mix of advantages and disadvantages for each, showing that the usefulness of recruitment strategies largely depends on the needs of one's investigation.

In said questionnaire study, data from 1,747 children yielded an overall prevalence of 22.2% for spectacle ownership and of 11.6% for spectacle ownership due to myopia (Study 3). Both prevalence rates were higher in females than males and in higher than lower age groups. For the prevalence of spectacles due to myopia, there was an especially large difference between the age groups of 9-11 years (10.0%) and 12-14 years (21.7%), and the between-gender difference was generally increased with age. While the detected prevalence rates align well with other questionnaire-based investigations, they were reduced compared to the prevalence of corrected myopia from our direct measurements in Study 1. This demonstrates the difficulty of obtaining accurate prevalence rates from questionnaire

investigations, though questionnaires seem well-suited to e.g. monitor prevalence changes over time or assess within-sample relationships (e.g., gender effects).

As light exposure is one modifiable factor implicated in myopia development, thoroughly assessing light-myopia associations is highly important, e.g. regarding prevention efforts. In reviewing respective investigations in Study 4, we found that the various utilized wearable light meters differ in their technical specifications, some of which are not public available, as well as how they are worn. The investigations vary in their methodology in aspects such as participant population, classification and proportion of myopic participants, and in- and excluded data, with potentially relevant aspects (e.g., season of data acquisition) sometimes not being reported at all. At the same time and despite the methodological variability between studies and devices, 1,000 lux is commonly used as an indoor-outdoor cut-off, often without prior validation. These methodological aspects might contribute to the variability in results, with some studies reporting light-myopia associations and others not, and should be considered when assessing or comparing investigations.

In Study 5, we directly compared measurements from simultaneously worn light meters, demonstrating a similar light exposure pattern but substantial variation in the absolute lux values. Sensitivity and specificity of the 1,000 lux indoor-outdoor cut-off as well as the ideal indoor-outdoor cut-off (calculated by maximizing the sum of sensitivity and specificity) also varied between devices. These results further underline the necessity to consider the light meters used as well as circumstances of data acquisition with regard to investigations of light-myopia associations. Furthermore, we recommend to consider calculating an indoor-outdoor cut-off from study-specific pre-measurements to achieve the best-possible indoor-outdoor distinction via lux measurements.

As commercially available light meters might not be ideally suited for one's research in terms of included sensors and other features, we investigated the feasibility of using a custom-made device in Study 6 that was developed according to requirements we defined. In conducting various measurements and data analyses – such as comparing the devices' measurements against each other, assessing their performance in different environments as well as potential indoor-outdoor cut-offs, and pre-processing as well as analyzing field test data with methodology typically used in light-myopia research –, we found that the devices are generally feasible for said data acquisitions and analyses. However, our prototypes (partly) exhibited technical failures as well as opportunities for improvement, and would need further development to be deployed in actual investigations of light-myopia associations. Due to the large availability of wearable light meters with diverse specifications, it may be more practical to use one of those for light-myopia research. However, especially for research areas with fewer usable devices available or in case of very specific requirements, it may be a viable option to develop and use a custom-made device.

4.2. Considerations Regarding the Research Objectives

In the following, I will assess the research objectives and discuss related topics based on the results from the individual studies of this dissertation.

4.2.1. Objective 1: Obtaining Current Myopia Prevalence Rates for Children and Adolescents in Germany

4.2.1.1. Myopia Prevalence Rates and Associations

In conducting Study 1, we added to the growing body of myopia epidemiology data, and obtained myopia prevalence rates of 8.4% for grade 3-4 primary school students and 19.5% for grade 8-10 secondary school students in Germany. The myopia prevalence difference between the younger and the older sample coincides well with the school myopia appearance age, which has e.g. been proposed to be between the ages of 9 and 11 (Gilmartin, 2004) as well as 8 and 14 (Morgan & Rose, 2005) years. Also, despite some variations, these prevalence rates were overall consistent with other (recent) data from Europe (see Table 2.6; e.g. Harrington, Stack, & O'Dwyer, 2019; Popović-Beganović et al., 2018; L. Yang et al., 2020). Regarding the situation in Germany, some data from refractive measurements has been published in the last few years (Kaymak et al., 2022; Truckenbrod et al., 2021), and the respective myopia prevalence rates are largely comparable to our findings in Study 1. While the myopia prevalence of 22% reported by Kaymak et al. (2022) for their grade 5-7 sample is slightly higher than that of our grade 8-10 sample, methodological differences such as a more liberal myopia cut-off and the necessity for active parental consent in their investigation might have played a role in this difference.

An increase in myopia prevalence over the next decades was predicted in 2016 both worldwide and for specific regions, including Western Europe (Holden et al., 2016). At the same time, a review and meta-analysis reported a stable or even slightly declining myopia prevalence for children and adolescents of white ethnicity (defined as people with white European ancestry who reside in Europe, America, Australia and New Zealand; Rudnicka et al., 2016). Importantly, investigations were grouped by ethnicity instead of geographical location – which are obviously not entirely congruent, despite the definition of white ethnicity as the predominant one for European investigations with no available ethnic specific prevalence rates (Rudnicka et al., 2016). For Germany, data from two waves (2003-2006 and 2014-2017) of the KiGGS questionnaire study suggests stable myopia prevalence rates in German children and adolescents in between (Schuster et al., 2020). The very similar prevalence rates of myopia (correction) between Study 3 and the KiGGS study (Schuster et al., 2020) hint at a continuously stable myopia prevalence in German youth, though there are

some constraints to both this interpretation as well as the prevalence rates derived from the questionnaire in Study 3 overall, which will be revisited in chapter 4.2.2.2. Furthermore, while I was only able to find very few refractive data from children and adolescents in Germany from the recent past, the fact that the myopia prevalence rates from Study 1 (acquired in 2021) are largely similar, and for the adolescents even slightly reduced, compared to those from Truckenbrod et al. (2021; acquired in 2014-2018), may also indicate that myopia prevalence rates did not increase in German youth over the last few years. Yet, while Truckenbrod et al. (2021) also utilized non-cycloplegic refractive measurements and a -0.75D SER myopia cut-off, methodological differences such as the measurement devices prevent complete between-study comparability. Instead of an increase in myopia prevalence in children and adolescents in Germany, Schuster et al. (2020) suspect a respective prevalence increase in young adults due to tertiary education, but could not assess this in their sample. An analysis of spectacle prescriptions, however, indicates that myopia prevalence is currently neither increasing in children and adolescents nor in young adults in Germany (Wesemann, 2017). Yet, investigations of both questionnaire and spectacle prescription data rely on indirect measures of myopia prevalence, and there has been discussion regarding their validity (see chapter 1.1.5). As will be described below (see chapter 4.2.2.2), however, repeating a questionnaire may be well-suited to detect changes in prevalence rates over time.

In spite of this, in order to obtain data that is as unbiased as possible, monitoring myopia prevalence and associations via direct measurements of refractive status would be beneficial. Especially with regard to the recent Covid-19 pandemic, comparing the Study 1 prevalence rates to more recent ones is worthwhile. Accelerated rates of myopic progression have been found in children and adolescents during the pandemic, which are assumed to be related to increased (decreased) near work (outdoor) activities (for a meta-analysis, see: Watcharapalakorn et al., 2022). Also, increased myopia prevalence has e.g. been found in children around the age of 7 years in Hong Kong both during and after Covid-19-related confinement measures, and time outdoors and near work/screen time did not return to pre-pandemic levels after restrictions were lifted (X. J. Zhang et al., 2023). Although there is only few data on the subject to date, other investigations also indicate persisting behavioral changes in relation to the pandemic, such as higher screen time and reduced physical activity both during and after school closures (though still during the pandemic) in Dutch children (ten Velde et al., 2021) or continued increased screen time in Canadian adults post- compared to pre-pandemic (S. Liu et al., 2023). The myopia prevalence rates from Study 1 are largely similar to prevalence rates obtained in Germany prior to the Covid-19 pandemic (Truckenbrod et al., 2021). Thus, at least for our sample of grade 3-4 and grade 8-10 school students, we did not find evidence of changes in myopia prevalence during compared to shortly prior to the pandemic. However, against the background of accelerated myopia development in other countries as well as potentially persisting myogenic behavioral changes

emerging from the pandemic, it is certainly relevant to monitor myopia development within the next years.

Our investigations also revealed interesting findings regarding factors associated with myopia, such as gender and age. A gender difference in myopia prevalence emerged in both Study 1 and Study 3, especially for higher grades and age groups, with females exhibiting higher prevalence rates as well as a more myopic refractive status than males. This is consistent with other literature (e.g., Czepita et al., 2019), and a review and meta-analysis reports that gender differences in myopia prevalence begin to appear around age 9 in white (and East Asian) populations and then become increasingly pronounced through adolescence, with an odds ratio of myopia of approximately 2 for females versus males aged 17-18 years (Rudnicka et al., 2016). Our results were in line with this: In Study 1, a slightly higher prevalence of myopia as well as a more myopic refractive status were found in boys than girls in grade 3, where the mean age was below nine years (8.85±0.78 years). In grades 4 (9.75±0.53 years) as well as 8 (13.98±0.77 years), 9 (15.04±0.80 years) and 10 (15.97±0.73 years), females exhibited a higher myopia prevalence and more myopic refractive status than males. Thereby, the between-gender difference was by far the highest in grade 10, with myopia prevalence being 20% higher in females than males, and a respective SER difference of almost 0.4D. Likewise, the questionnaire data from Study 3 exhibited a higher prevalence of spectacles due to myopia in females than males in all age groups but 3-5 years, though both the overall prevalence of spectacles due to myopia as well as the gender difference were negligible for the 0-2-year-olds. Furthermore, said gender difference was generally increased in older compared to younger age groups, with the exception of it being more pronounced in the 9-11-year-olds than the two older age groups (see Figure 2.6). The reasons for the gender difference in myopia prevalence are not yet well understood, and both biological and behavioral factors have been proposed (Czepita et al., 2019). Although further research into the origins of this difference is recommended, it is important to acknowledge its existence, particularly when designing myopia information and prevention campaigns. With regard to age, we found an especially large myopia prevalence difference between grades 8 and 9 (9.9%) in Study 1, which was even higher than the difference between grades 4 and 8 (3.0%). Data acquisition took place within the first four months of the school year, and the grade 8 (grade 9) students in our sample were aged 13.98±0.77 years (15.04±0.80 years). Thus, while these ages lie at the upper end or even beyond the 8-14 years during which school myopia has been proposed to appear (Morgan & Rose, 2005), grades 8 and 9 may be especially relevant with regard to myopia onset in a German-like school system. This finding may also have implications for measures such as myopia diagnostic campaigns. For example, it indicates that both diagnostic and health-education campaigns on myopia might be especially useful around grade 9 in a German-like school system.

4.2.1.2. Uncorrected Myopia

The alarmingly high rates of uncorrected myopia we detected in Study 1 – with 51.2% of the myopic grade 3-4 students and 43.3% of the myopic grade 8-10 students being uncorrected – are of particular note and especially worrying given that uncorrected myopia was often substantial (see Figure 4.1).

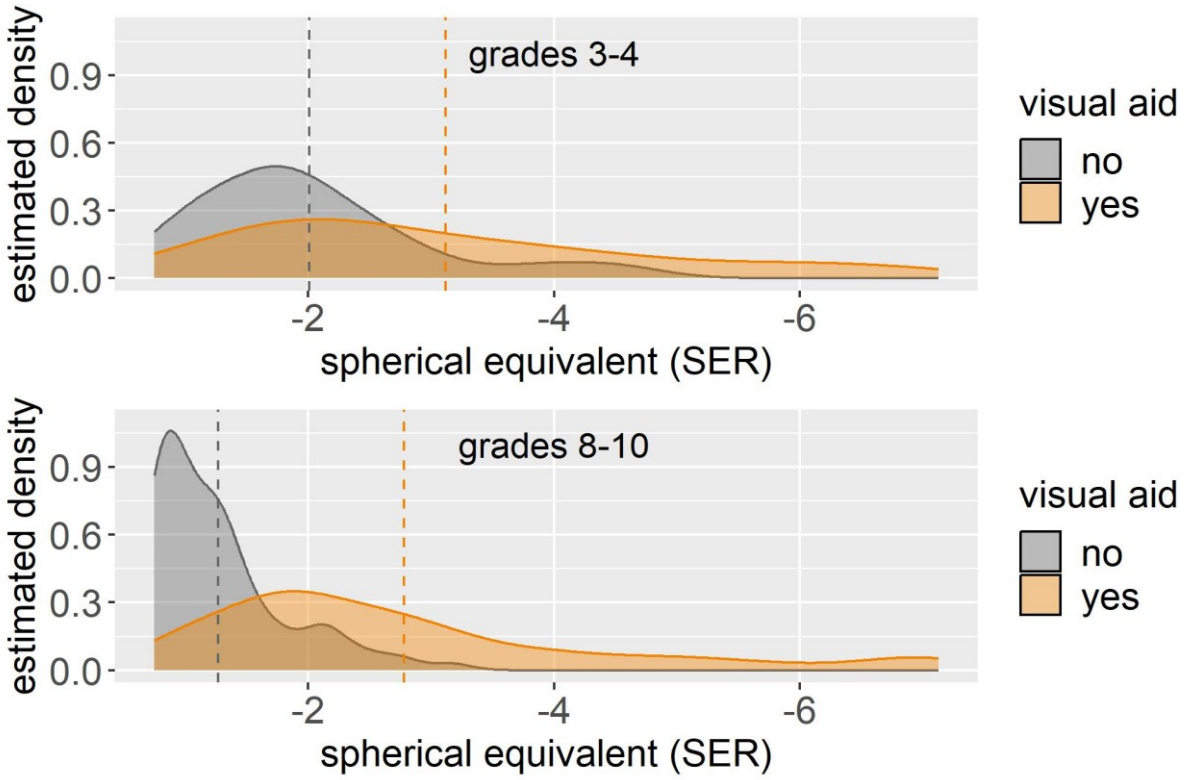


Figure 4.1. Density plots of the spherical equivalent distribution of corrected and uncorrected myopic participants from Study 1. Dashed vertical lines represent the respective subgroup's mean SER. The depicted SER range covers all SER values that can be exhibited from a myopic participant in this study (between -0.75D and -7.125D). Data from two (one) myopic participants from grades 3-4 (grades 8-10) are excluded due to missing SER values.

This was particularly true in grades 3-4 (uncorrected myopia mean SER: -2.01D±1.64D; corrected myopia mean SER: -3.12D±0.93D). As the grade 3-4 participants were outside or at the lower end of the age range for "school myopia" development, it is likely that the respective myopic participants predominantly had a type of myopia with a stronger genetic component and an onset very early in life (Spillmann, 2020). Thus, at least some of the myopic grade 3-4 students had likely been myopic for some time already, including those lacking correction – which makes the severity of their myopia even more alarming. In comparison, the severity of myopia was reduced in the (uncorrected) myopic participants in

grades 8-10 (uncorrected myopia mean SER: -1.27D±0.53D; corrected myopia mean SER: -2.58D±1.72D). This makes sense insofar as many of the respective myopic participants had likely only recently developed "school myopia". But even in grades 8-10, a considerable proportion had uncorrected myopia with an SER well beyond the myopia cut-off, and rates of uncorrected myopia were overall also still high when applying a more conservative myopia cut-off of ≤ -1D SER (48.7% in grades 3-4 and 32.7% in grades 8-10).

High rates of uncorrected myopia have been found elsewhere, too (Choy et al., 2020; Popović-Beganović et al., 2018; Jianyong Wang et al., 2020; M. Yang et al., 2018). Failure to correct myopia is problematic because it can adversely affect educational outcomes as well as quality of life (Sankaridurg et al., 2021) and its economic costs far exceed the costs associated with correcting myopia (Naidoo et al., 2019). Furthermore, undercorrection of myopia seems to accelerate its progression compared to full correction (Logan & Wolffsohn, 2020).

Myopia remains uncorrected for multiple reasons, among them lack of myopia awareness and – frequently observed with adolescent participants in Study 1 – unwillingness to wear a visual aid. Lack of awareness could be counteracted with more frequent refractive error screenings. In Germany, recommendations for visual check-ups only include one before the age of 16 and then one about every 10 years for complaint-free 7-39-year-olds without ametropia or eye disease or known risk factors for either one (Berufsverband der Augenärzte Deutschlands e.V. & Deutsche Ophthalmologische Gesellschaft e.V., 1998). The AOA, on the other hand, recommends annual comprehensive eye exams for 6-17-year-olds (American Optometric Association, n.d.). In Study 3, we found that only about 36% of spectacle-free children and adolescents aged 9-11 years and above had been assessed regarding potential spectacle need within the last year. Similar results were found in the UK: During a 18-months study period, only 34.4% of individuals aged < 16 years of the study population received a sight test of the National Health Service, despite sight tests being free of charge for that age group (Swystun & Davey, 2021). With regard to the high rates of uncorrected myopia in Study 1 and the potential consequences thereof, implementing measures to increase the percentage of children and adolescents receiving regular visual check-ups would be worthwhile. One such measure may be enhancing the frequency of visual check-ups in the German recommendations. However, changing recommendations alone will likely not be sufficient. Implementing refractive screenings in a way that relieves families from scheduling appointments themselves could be particularly effective. For instance, regular refractive screenings could be conducted in schools, which would also be beneficial if an overall increase in the frequency of visual check-ups would put too much strain on the healthcare system's resources.

The issue of children and adolescents being unwilling to wear recommended visual aids has been discussed before. Multiple (psycho)social barriers have been identified for spectacle wear, such as (fear of) discrimination or bullying (for reviews, see: Congdon et al., 2019; Sankaridurg et al., 2021). What is more, even parents' perception of spectacles as a social stigma can be a barrier to children's spectacle wear (Senthilkumar et al., 2013). Performing in-school refractive screenings for complete grades may be helpful with regard to (psycho)social barriers to spectacle wear. Especially for adolescents, in-school screenings could help normalize the need for refractive correction and prevent singling out individual students, as multiple students would likely be informed of their need for visual correction simultaneously. Indeed, a school-based program that provided corrective lenses showed that students' willingness to wear new spectacles might increase when their peers start wearing them as well (Dudovitz et al., 2016). Another (additional) possibility to increase children's and adolescents' willingness to wear visual aids may be peer-group targeted health education with regard to refractive error.

Finally, the socioeconomic situation might be another factor in explaining the prevalence of uncorrected myopia. In Study 1, we found a 22% lower rate of uncorrected myopia in primary schools with a low compared to those with a high social burden. As this finding is based on 41 participants only, it should be considered preliminary and with caution. However, comparable results have been reported before. For example, among < 16-year-olds in the UK, those living in the least deprived quintile have been found to be 23%-26% more likely to have a sight test than those in the most deprived quintile (Shickle et al., 2018; Shickle & Farragher, 2015). Furthermore, ethnic minorities in the USA exhibit a higher prevalence of both un- or undercorrected refractive error (Qiu et al., 2014) as well as reduced eye care (Kemper et al., 2004). While our preliminary finding of uncorrected myopia being especially prevalent in children with a high social burden should be investigated further, the overall notion of individuals with a higher social burden being disproportionally affected by lack of eye health care and refractive correction should be considered in interventive measures. For example, targeted health education may be useful in this regard as well.

4.2.2. Objective 2: Assessing the Application of Online Questionnaires for Myopia Prevalence Research

4.2.2.1. Recruitment Strategies for Online Questionnaires

In Study 2, we compared recruitment strategies for online research. Importantly, we recruited participants for a short questionnaire and subsequently asked them to also complete a long questionnaire. Most analyses regarding recruitment strategies in Study 2 relate to the short questionnaire, but we also assessed the percentage of participants completing the long questionnaire. Table 4.1 presents a brief overview over the various aspects addressed in the comparison as well as how the strategies performed regarding each aspect in comparison with each other. In the following, I will briefly revisit each strategy and present conclusions and recommendations associated to each strategy's (dis)advantages.

In CLUSTER, we asked schools and daycare centers selected via multistage cluster sampling to advertise our study. Despite the high workload and extremely unfavorable questionnaire-workload ratio (i.e., number of included questionnaires per hour of work), CLUSTER is an overall viable strategy to obtain a large sample, if one can manage the high associated workload, because of its many recruitment opportunities. It is also not associated with high monetary costs. In our case, monetary costs could even have been nonexistent with even more increased workload. Generally, kindergartens and primary schools were more likely than secondary schools to advertise our study. It is thus advisable to specifically focus recruitment on secondary schools if one aims at balanced age groups, and doing so might even lead to a representative sample in not only gender but also age. One might also oversample schools or areas with characteristics for which one expects low participation. For example, participation biases regarding educational status have been reported for health surveys, participants with low educational status thereby being underrepresented (Berra et al., 2007; Klijs et al., 2015). General recruitment success in CLUSTER as well as the percentage of participants who additionally complete the long questionnaires might be increased with a participation incentive, as CLUSTER was the only utilized strategy without a voucher raffle, which probably reduced motivation compared to the other strategies. However, this may be prevented by legal restrictions regarding recruitment at schools. I also recommend to assume a long lead time if approval from authorities – in our case, the federal states' ministries concerned with education – is needed for recruitment.

Table 4.1

Overview and Results of Aspects Assessed per Strategy in Study 2

strategy	questionnaires		short-to-long questionnaire (%)	participation rate (%)	child data rate (%)	representativeness		costs per child (€)	workload (*h*)	questionnaire-workload ratio
	short (*N*)	long (*N*)				gender	age			
CLUSTER	206	18	8.7	2.8	2.5	yes	no	0.30	125	1.6
KSW	82	35	42.7	n/a	n/a	yes	no	0.00	≤ 2	41.0
NETWORK	500	82	16.4	n/a	n/a	no	no	≤ 0.02	14	35.7
TARGET	137	49	35.8	11.8	11.8	yes	yes	2.05	11.5	11.9
WILD	157	37	23.6	n/a	n/a	yes	no	0.00	46	3.4

Note. Data taken from Study 2. The individual aspects are rated best (light gray) to worst (dark gray) between the recruitment strategies. If there are less than five ratings (because less than five strategies can be rated or several strategies are rated the same), the coloring still starts at the lightest gray and does not go until the darkest one. In case of yes/no ratings, only the lightest and the darkest gray are used. Cells marked "n/a" are not included in the rating. "short-to-long questionnaire" denotes the percentage of short questionnaire participants that also completed the long questionnaire. "questionnaire-workload ratio" denotes the (approximated) number of included short questionnaires per hour of work.

KSW describes the recruitment via a website advertising studies in need of child and parent participants. With its low workload, extremely favorable questionnaire-workload ratio and nonexistent monetary costs, KSW recruiting can be a great additional source, and especially valuable if participants need to be very motivated. High participant motivation is not only reflected by the fact that KSW participants actively found the study on a website advertising opportunities to participate in research, but also in the high percentage of participants who also completed the long questionnaire. If a large sample is needed, especially including (parents of) older children and adolescents – who were underrepresented in KSW – only using a recruitment strategy like KSW may not be sufficient. This is at least the case if the respective website is not very widely known, which, presumably, was the case during our recruitment. Furthermore, a sample recruited in this manner is likely biased: Participants with high educational status may e.g. be overrepresented as the website was primarily advertised within university-affiliated communities. If the website was more well-known, however, a strategy like KSW may be an even better recruitment opportunity for large(r), more balanced samples.

NETWORK indicates the questionnaire distribution in our own personal and professional networks and produced the most short questionnaires by far while costing almost nothing (apart from the raffle). Overall, NETWORK was the best strategy to recruit a high number of participants, and while we were not able to calculate participation and child data rates for NETWORK, they were likely substantially higher than those of CLUSTER. It is probably helps participation motivation if one is connected to the researchers – though it seems that NETWORK participants were primarily motivated for the short questionnaire, but not enough to also complete the long one. Also, sample representativeness likely depends on the researchers' networks. In our case, there were more parents with older than younger children, and the NETWORK sample's age distribution was thus not representative of the German population. This was also the case for the gender distribution. Amongst others, we speculated if this had to do with more NETWORK recruitment in locations with more parents of girls than boys. Like for CLUSTER, we assume an overrepresentation of high educational status in NETWORK, as a large part of the researchers' networks is university-affiliated. Generally, if a balanced sample with regard to various characteristics is important, NETWORK recruiting is likely problematic. Yet, even with the possibilities of online recruitment, recruiting in own networks still is a good way to achieve large samples.

In TARGET, we sent postal participation invitations to randomly selected families within the city of Dortmund. TARGET was the most expensive strategy by far, but given the monetary resources, it seems to be a great way to effectively achieve a representative sample – especially due to the high participation and child data rates. In addition, the currently moderate questionnaire-workload ratio would likely increase even more had we recruited more participants via TARGET: As a lot of work included initial preparations, the workload

does not increase proportionally with the number of letters sent. In TARGET recruiting, one can also rather easily adjust for potential biases by oversampling regions where the trait for which on assumes underrepresentation (e.g. through lower participation rates) is more prevalent. For example, in KiGGS, samples were taken from population registries, and children and adolescents without German citizenship were oversampled – among others to adjust for the expected lower response rates from this population (Hoffmann et al., 2018).

Lastly, in WILD, we distributed the questionnaire online in forums, Facebook groups and via Instagram influencers. While less effective than most strategies in terms of questionnaire-workload ratio, WILD was overall moderately effective in recruitment. Especially if one plans on doing this type of recruitment regularly, it may be worthwhile to try to establish contacts with widely-known Instagram influencers willing to advertise studies more than once, thus reducing the time spent with recruitment for each individual study. Younger children were overrepresented in WILD, probably because young adults are the most represented age groups on Instagram and Facebook (We Are Social et al., 2023a, 2023b) and due to potentially especially new parents seeking advice in online forums. If a balanced age distribution is important, one might consider oversampling in online networks and on websites that specifically target parents of older children and adolescents.

When interpreting the findings regarding the different recruitment strategies, one needs to keep in mind that no (CLUSTER) or small (all other strategies) incentives were provided for participation. Had there been guaranteed compensation, participation rates would probably have been higher. On the other hand, guaranteed compensation for participation in (online) research can elicit other problems such as survey fraud (Singh & Sagar, 2021), especially so if data quality cannot reliably be assessed or controlled, which was the case in our questionnaire. In the absence of guaranteed compensation, however, we estimated the risk of participants completing the questionnaire(s) more than once or with fake answers as relatively low.

Overall, the tested recruitment strategies have different advantages and challenges, and it depends on factors such as resources and the needs of a given study which of the discussed – or any further – strategies is the best option.

4.2.2.2. Epidemiological Research with Online Questionnaires

We found inconsistencies when comparing the myopia prevalence rates obtained from autorefraction data in Study 1 to the rates of participants owning spectacles due to myopia in Study 3. On first sight, the prevalence rates seem largely similar: The autorefraction measurements revealed myopia prevalence rates of 8.4% (9.30±0.78 years) as well as 19.5% (14.99±1.12 years). Meanwhile, the prevalence rates of spectacles due to

myopia – for the age groups fitting age ranges considered in Study 1 – were 6.3% (6-8-year-olds) and 10.0% (9-11-year-olds) as well as 21.7% (12-14-year-olds) and 26.5% (15-17-year-olds). However, the autorefraction prevalence rates include a large portion of myopic individuals without a visual aid that would not be captured via the questionnaire. To fit the myopia prevalence rates obtained via autorefraction, the prevalence rates of spectacle ownership due to myopia from the questionnaire would thus need to be substantially lower.

Due to potential participation biases in the questionnaire, we consider the autorefraction data to be more reliable for prevalence estimation. Among others, we assume an overrepresentation of participants with high educational status in the questionnaire data, which might have played a role in the presumed bias in the Study 3 myopia prevalence data: Not only have people with low educational status been found to be underrepresented in health surveys before (Berra et al., 2007; Klijs et al., 2015), but as discussed above, especially some of our recruitment strategies for the questionnaire may have favored parents with high educational status. This is especially detrimental with regard to myopia prevalence estimations, because a positive association between myopia and education has repeatedly been found (see chapter 1.1.6.2). Furthermore, in the younger sample in Study 1, we found preliminary evidence that myopic children with a higher social burden are more likely to lack visual correction compared to myopic children with a lower social burden. This may increase the differences in the results between Study 1 (autorefraction measurements) and Study 3 (questionnaire), as only children with corrected myopia would be captured in the questionnaire. While parental educational status per se is not a factor in the calculation of the social index of schools (Schräpler & Jeworutzki, 2021) we used to estimate social burden, there generally is a negative association between educational status and indicators of the social index, such as poverty (Hofmarcher, 2021). Thus, while we did not assess educational or socioeconomic status in our current questionnaire, doing so would probably be helpful with regard to myopia research.

Naturally, our autorefraction data has limitations as well (see Study 1), the main concern being myopia overestimation due to the absence of cycloplegia, which has been found before (Grzybowski et al., 2020; Rudnicka et al., 2016). However, for Plusoptix devices and especially in non-hyperopic individuals, good measurement accuracy has repeatedly been shown for non-cycloplegic refractive measurements (Fogel-Levin et al., 2016; Ghadimi et al., 2024; Payerols et al., 2016; Teberik et al., 2018; Wilson et al., 2022). We further aimed at compensating for a potential myopia overestimation by increasing the myopia cut-off to ≤ -0.75D SER from the usual -0.50D. Also, a potential overestimation of myopia prevalence rates in Study 1 does not explain the discrepancy between the Study 1 and Study 3 prevalence rates, because the former are generally lower than the latter. Thus, potential inconsistencies due to non-cycloplegic autorefraction do not underly said discrepancy.

The comparison of our autorefraction (Study 1) and questionnaire data (Study 3) thus suggests that questionnaire estimates of myopia prevalence suffer from a substantial upward bias. Overall, more research is needed to assess and correctly interpret epidemiological questionnaire data. More data from direct measurements may be useful in this regard, which will be expanded upon in chapter 4.3. Yet, despite their disadvantages for estimating absolute prevalence rates, questionnaires may be a helpful tool to monitor the development of (myopia) prevalence rates or assess relationships within the measured data. In Study 3, we for example replicated typical findings in myopia research, such as the prevalence rates of (spectacle ownership due to) myopia continuously increasing throughout childhood and adolescence, with an especially pronounced difference between the age groups of 9-11 and 12-14 years, coinciding with the typical school myopia onset age (Gilmartin, 2004; Morgan & Rose, 2005). Our study thereby reinforces the notion of questionnaires as a valuable tool to gain important, additional insights into a population's refractive problems (Landmann & Bechrakis, 2013). As described above, for example, the similarity between the prevalence rates from the Study 3 questionnaire and those of the KiGGS study (Schuster et al., 2020) potentially suggest a continuously stable myopia prevalence in German youth since 2003-2006. However, this should only be considered as a first hint, especially since we also interpreted the similarity between our and the KiGGS data as support for the usefulness of our questionnaire. Furthermore, to reliably monitor prevalence development using questionnaires, it is important to keep the methodology of data acquisition constant between acquisition phases, amongst others to keep (potential) biases consistent, and there were substantial differences in the methodology between our study and the KiGGS study. Repeating our questionnaire in a few years may thus be helpful to further assess the current development of myopia prevalence rates. Lastly, the constraints of (potential) participation biases with regard to the questionnaire data's generalizability should also be considered: For example, if individuals with higher educational status are actually more likely to participate in our questionnaire than others, and – theoretically – the changes in myopia prevalence over time were to differ between (children of) individuals with and without higher education for some reason, the questionnaire's data on myopia prevalence development would not be generalizable. Yet, when keeping this in mind, questionnaires may be a very useful additional tool for epidemiological research, especially as recruitment and data acquisition generally require less financial and other resources than many other research methodologies.

4.2.3. Objective 3: Extending Methodological Insights into the Usage of Light Meters in Myopia Research

4.2.3.1. Comparability of Light Meters and Research Methodology

The literature review (Study 4 – Hönekopp & Weigelt, 2023) showed that the light meters used in research on light-myopia associations were diverse in their specifications, such as (intended) wearing location, available light measurements, lux measurement range or spectral sensitivity. Thereby, the spectral sensitivity of their "lux" measurements does not necessarily comply with the official definition of lux (Figueiro et al., 2013; Ohno et al., 2020), sometimes exhibiting considerable differences between the spectral sensitivity of the human eye and the respective sensor, e.g. in case of the HOBO Pendant Temp/Light data logger (Onset Computer Corporation, 2012). Despite substantial effort, we were unable to obtain all potentially relevant specifications regarding light measurements for all devices considered in Study 4 (Hönekopp & Weigelt, 2023). This lack of information includes commercially available devices (at the time).

The between-device variability seems to have a real-life impact. Earlier research already demonstrated measurement differences between different light meters (some of them in comparison to photometer measurements; Figueiro et al., 2013; Howell et al., 2021; Joyce et al., 2020), similar light meters at different body positions (Aarts et al., 2017; Figueiro et al., 2013; Wen et al., 2021), and different light meters at different body positions (Bhandari et al., 2021; Read, Vincent, et al., 2018; van Duijnhoven et al., 2017). However, especially differences between devices worn at different body positions have usually not been assessed systematically and over a longer time period before. Recently, one large and systematic investigation of three wearable light meters (Clouclip M2, Actiwatch 2, and HOBO Pendant UA-002-64) was published as part of a dissertation (Phan, 2022). Therein, poor correlations and significant differences between the devices' light intensity measurements were found. By systematically conducting simultaneous measurements with multiple light meters in the field from morning to evening while also tracking each indoor-outdoor location change, Study 5 confirmed and expanded the measurement differences found in earlier research: We detected considerable differences in the measured (absolute) lux values. Furthermore, the sensitivity (i.e., percentage of actual outdoor time correctly identified by ≥ cut-off value) and specificity (i.e., percentage of actual indoor time correctly identified by < cut-off value) of the commonly used 1,000 lux indoor-outdoor cut-off as well as the calculated ideal indoor-outdoor cut-offs varied largely between devices. For example, for the same measurement day and the 1,000 lux indoor-outdoor cut-off, the Actiwatch 2 exhibited a 49.1% sensitivity and 91.7% specificity, while the HOBO Pendant UA-002-46 mounted on a pedestal exhibited a 96.3% sensitivity and a 88.9% specificity. For all devices, high sensitivity and specificity values for indoor-outdoor distinction could be achieved when calculating their ideal lux

indoor-outdoor cut-off via ROC curve analyses and maximizing sensitivity and specificity. The ideal lux cut-off also showed considerable between-device variation, varying between 260 lux and 1,380 lux on day 1 as well as 310 lux and 2,590 lux on day 2.

Importantly, high sensitivities and specificities with the ideal indoor-outdoor cut-off could not only be achieved when calculated from the same data that was used to obtain it. Instead, for the devices of which we have data from two days (with largely similar weather conditions), sensitivities and specificities of the ideal cut-off were also high when we calculated them for one day with the ideal lux cut-off calculated from the other day. Especially for the Actiwatch 2 and Actiwatch Spectrum PRO, the other day's ideal cut-off also substantially outperformed the 1,000 lux cut-off in terms of sum of sensitivity and specificity for indoor-outdoor classification. For the HOBO Pendant UA-002-64 devices, the other day's ideal cut-off also outperformed the 1,000 lux cut-off in three out of four cases, though only very slightly so. In the fourth case, the sum of sensitivity and specificity was slightly lower for the other day's best cut-off than the 1,000 lux cut-off. To assess which devices may (especially) profit from this approach (under which circumstances), more methodological investigations are needed. Overall though, when it is of interest to accurately distinguish indoors versus outdoors via lux measurements, our findings in Study 5 show that it could be helpful to calculate an indoor-outdoor cut-off for one's investigation from data measured with similar device and under similar circumstances as in the real data acquisition instead of simply using the common 1,000 lux cut-off. Comparably, ideal indoor-outdoor cut-offs largely deviating from 1,000 lux have been found before: For example, 240 lux (Flynn et al., 2014) and 110 lux (Tandon et al., 2013) were determined as the best indoor-outdoor cut-offs in two investigations on measuring light levels in pre-school children with the ActiGraph GT3X+ device.

Apart from the light meters, there was also considerable variation in the methodology of investigations on light-myopia associations, for example with regard to geographical location, aspects of the participant population, or data analysis. The existing diversity in their results on light-myopia associations with no apparent patterns with regard to many factors we found in Study 4 (Hönekopp & Weigelt, 2023) is not surprising, especially because at the time of conducting Study 4 (Hönekopp & Weigelt, 2023), only 20 publications met our review's inclusion criteria. While the methodological aspects investigated in Study 4 (Hönekopp & Weigelt, 2023) were for the most part thoroughly described in the individual publications, important information was missing in a few cases, for example with regard to season and geographic location of data acquisition or the exact times (of day) considered for light data analysis. In this regard, it is not only important to choose the best methodology for one's research, but to also thoroughly report it. Furthermore, one should choose the light meter that best fits the study's requirements, and consider aspects of methodology and utilized light meters when comparing investigations. In theory, investigations could be

compared more easily if everyone used similar devices. This is, however, neither likely nor even desirable for many reasons. For example, there may be differing needs of a study's data acquisition situation or study population that may amongst others relate to aspects of wearability, battery life or included sensors.

Interestingly, even though many light meters are used in various ways and different settings in light-myopia research, especially one methodological aspect is often kept extremely similar: In most studies, a 1,000 lux cut-off for indoor-outdoor distinction was used, usually without own prior validation (see Study 4 – Hönekopp & Weigelt, 2023). However, as described above, we detected large variations between devices' sensitivity and specificity values of the 1,000 lux cut-off as well as the ideal indoor-outdoor cut-off in Study 5. These simultaneous measurements did not even take into account the possibility of other between-study differences that might influence the accuracy of the indoor-outdoor cut-off, such as different weather conditions. Thus, the between-study comparability regarding indoor-outdoor distinction based on the same cut-off value is questionable, as is the ability of the 1,000 lux cut-off to reliably classify indoors versus outdoors.

Yet, even when calculating an own indoor-outdoor cut-off ideally targeted to one's specific study, there may well be situations where indoors is brighter than outdoors, even at daytime. Such reversals have been reported before (Dharani et al., 2012), and were also confirmed in the category measurements of Study 6. Thus, especially if one is interested in classifying actual indoor versus outdoor time – as compared to time spent in higher versus lower light levels –, one may want to consider using other (additional) measures to achieve an accurate distinction. Actually classifying indoors versus outdoors may, for example, be of special interest if one (also) investigates other environmental aspects than brightness potentially implicated in myopia development (Howell et al., 2021), or if one is assessing thresholds for required time spent outdoors in outdoor intervention programs. Since solar radiation extends into the UV spectrum while that of artificial light sources generally does not, UV light may be one potential variable to consider for indoor-outdoor classification. In fact, the overlap between indoor and outdoor categories was reduced for UV light compared to lux measurements in the category measurements in Study 6. Also, using UV light measurements for indoor-outdoor classification achieved a slightly more accurate classification than using lux measurements in the test measurements. Vivior Monitor can also measure UV light and demonstrated high sensitivity and specificity values when distinguishing indoors from outdoors via the UV light measurement in Study 5 – though its ideal lux cut-off was still slightly more successful for the indoor-outdoor distinction than its ideal UV light cut-off. Furthermore, approaches to combine different measurements for indoor-outdoor distinction have been pursued in recent years, for example by considering both lux and UV light exposure (Fan et al., 2022) or lux, UV light and step data (Ye et al., 2019). The latter thereby used a machine learning algorithm to create a classification system using

these three variables (Ye et al., 2019). In the future, approaches such as this might potentially be expanded to other variables such as time of year or location of data acquisition to categorize data more reliably.

Overall, we not only found that the light meters utilized in light-myopia research differ in their specifications – sometimes considerably so –, but also that these differences have an actual impact on their measurements. Despite this not being the focus of this dissertation, it is interesting to note that even devices of the same type can differ substantially in their measurements, and it may be helpful to calibrate them prior data acquisition (Markvart et al., 2015). Furthermore, investigations on light-myopia associations exhibit considerable differences in their methodology and specifications. More methodological research with regard to light meter measurements would thus be advisable, for example with regard to cut-off values and assessed variables for indoor-outdoor distinction. Also, researchers should thoroughly report and consider methodological aspects when conducting or assessing investigations on light-myopia associations.

4.2.3.2. Feasibility of Developing a Custom-Made Device

In research with wearable devices, one might come across the situation that none of the available devices combines all the features that would be ideal for one's investigation. Furthermore, as discussed before, not all potentially relevant information on device features may be disclosed for commercially available devices, and manufacturers may change device specifications, even without prior notice (Study 4 – Hönekopp & Weigelt, 2023; Markvart et al., 2015). Therefore, Study 6 investigated the feasibility of developing a custom-made wearable device, specifically targeted to light-myopia research, whereby two electrical engineers developed, built and programmed the devices according to pre-set requirements.

Overall, the developed prototypes performed adequately and included the required technical specifications. The devices utilized in the field test showed good and excellent reliability for static and moving device comparison measurements, respectively, for both lux and UV light. For lux, these could be assessed with regard to prior research, and while our prototypes' reliability was somewhat reduced compared to that of the Actiwatch 2 in the moving condition (Read et al., 2014), it was comparable to that of Clouclip in static conditions (Wen et al., 2021). Likewise, the data acquisition in the seven-day field test with six participants was also generally successful. However, participants assessed the device as sometimes being (slightly) disruptive and potentially awkward in social situations. As the field test was conducted at a time during which social gatherings were restricted due to the Covid-19 pandemic, especially the noticeability could potentially be a larger problem at other times. Participants also commented on device wearability, and the issues that they described

resembled those reported in another study with regard to a similarly worn device (Phan, 2022). Lastly, we succeeded in performing typical data preparation and analysis procedures, as well as in calculating an ideal indoor-outdoor cut-off as described in Study 5 for both lux and UV light measurements.

Yet, in addition to those listed above, there were some further issues with regard to the device prototypes. These encompassed a few technical failures as well as practical aspects such as short battery life or the ambient light sensor's current upper lux measurement limit. The latter, while suitable for common analyses such as indoor-outdoor distinctions or time spent in different light levels usually distinguished in light-myopia research (Bhandari et al., 2022; M. Li et al., 2021; Ostrin, 2017; Ostrin et al., 2018; Read et al., 2014, 2015; Wen et al., 2020; Wu et al., 2018), would pose problems for analyses such as cumulative or average lux exposure (Alvarez & Wildsoet, 2013; Mirhajianmoghadam et al., 2021). With regard to the former, it should be noted though that even commercially available devices such as Clouclip or Vivior Monitor exhibit a comparably short battery life of ca. 35 hours and up to 16 hours, respectively (Study 4 – Hönekopp & Weigelt, 2023).

Many of the encountered issues could potentially be – and partly already have been – solved with further revisions of the prototype. Yet, while theoretically usable for research on light-myopia associations, our device would need further development and testing to really be feasible for use in field studies. As there are many devices (commercially) available for research on light-myopia associations (Study 4 – Hönekopp & Weigelt, 2023), it would likely be more practical to choose one of those, especially as they cover a range of different options, e.g. with regard to additional measurements or ways of wearing. It is thus likely that one of them will generally fit the requirements of one's investigation. With regard to way of wearing, however, it should be noted that there were multiple options for wrist-worn light meters at the time of conducting Study 4 (see Table 3.1 in Study 4 – Hönekopp & Weigelt, 2023). Yet, of those, the Actiwatch devices were the only ones commercially available at the time, which were recently removed from the market. Thus, there may currently be a gap with regard to commercially available wrist-worn light meters – though at the time of conducting Study 4 (Hönekopp & Weigelt, 2023), the developers of one of the other wrist-worn devices included in the review were already planning to put their device on the market. Also, while wrist-worn devices certainly have advantages over others, e.g. in terms of wearability and being less noticeable and/or disruptive, their light intensity measurements do not seem to be comparable to those at eye level (Hartmeyer et al., 2022). Thus, they may not be ideally suited if one aims at measuring eye level-like light intensity for light-myopia research.

Lastly, while it seems more convenient to use a commercially available device for light-myopia research, Study 6 also demonstrated that it is possible to develop a bespoke wearable device for field studies. Thus, in case a planned investigation has very specific needs

regarding device features or for research areas with fewer devices (already) available on the market, creating and using a custom-made device may be a viable option.

4.3. Implications for Future Research and Public Health

Finally, various implications with regard to both practice and public health as well as further research arise from the findings within this dissertation, which I will present in the following. In doing so, I also present specific recommendations for action with regard to the aspects that this dissertation has addressed. While these recommendations are in no way all-encompassing, they may well provide starting points for further actions.

In terms of **myopia prevalence estimates**, I recommend to continuously monitor the prevalence development in (German) youth. To generate data that is comparable over time, it would be advisable to conduct refractive screenings in children and adolescents every few years while keeping the methodology constant. While it is the gold standard to perform objective refractive measurements under cycloplegia, especially in children (Flitcroft et al., 2019; Grzybowski et al., 2020), non-cycloplegic measurements as used in Study 1 may be helpful to reduce participation biases and ensuring a (more) representative sample: Due to their non-invasive nature and when additionally ensuring immediate data anonymization, it may be possible to implement an opt-out procedure for parental consent. When measuring in schools, this would allow the measurement of all students whose parents do not actively opt out, rather than only those whose parents provided written consent. Also, with the procedure from Study 1, the expenditure required for the actual refractive screenings is limited. From our experience, recruitment of the schools and coordinating the measurements with them was rather resource-intensive, and thus it may be helpful both in terms of constant research methodology and resource management to perform refractive screenings at the same schools every few years. Yet, one might also want to sporadically include other schools as a control, since the awareness regarding refractive errors and correction might increase within a school in case of regular refractive screenings, and so the sample might not be representative of the population with regard to e.g. the prevalence of uncorrected myopia.

Furthermore, this dissertation very clearly demonstrates the necessity of reducing the high prevalence rates of **uncorrected myopia** in German youth. Myopia correction has the potential to mitigate a range of negative consequences than can arise from myopia, and thus the high rates of uncorrected myopia that we found in Study 1 leave a lot of room for improvement. Various approaches could be taken to reduce this problem. Generally, further research into associations of uncorrected myopia would be advisable – for example to expand upon the finding from Study 1 regarding children with a higher social burden potentially being disproportionally affected from uncorrected myopia. Respective

information may then be used to create and optimize intervention programs, specifically taking into account potential needs and barriers of underserved communities. With regard to specific public health measures, one could for example create school-based information campaigns targeted at educating adolescents or (parents of) younger children about myopia and potential consequences of failing to correct it. This is especially relevant since in Study 1, many adolescents with uncorrected myopia were aware of their vision problems, but unwilling to wear spectacles. Likewise, school- or grade-wide refractive screenings could be performed, especially for adolescents. These screenings, which can be conducted at a reasonable cost and can also be used to monitor myopia prevalence for research purposes, should at least continue up to grade 9 (in a German-like school system), as we found a much higher myopia prevalence in grade 9 than 8 in Study 1. As explained above, such screenings can be conducted with a reasonable amount of expenditure and could simultaneously be used to monitor myopia prevalence development. Furthermore, a school-based approach to reduce uncorrected vision problems has been found to increase students' willingness to wear corrective lenses before (Dudovitz et al., 2016). Lastly, the frequency of (recommended) visual assessments during childhood and adolescence in Germany should be increased or, as advocated for by Kaymak et al. (2022), the general preventive medical check-ups for children and adolescents that exist in Germany should be expanded to include a myopia check-up.

With regard to **recruiting participants for online research**, this dissertation presents advantages and disadvantages of various of recruitment strategies that can be evaluated against the background of the needs and specifications of one's study. For example, when primarily requiring a strategy that is efficient in terms of participants per recruitment time, approaches such as posting the study on a website for potential participants and distributing it in the researchers' personal and professional networks are especially beneficial. If workload is less of a concern, distribution via schools and kindergartens would be well-suited. Where representativeness is particularly desirable, sending postal invitations to randomly chosen people was found especially useful, but this strategy was relatively expensive. Similar considerations can be made for various other factors, a number of which we investigated in Study 2. Thus, the findings from Study 2 may be useful to help choosing the strategies that best fit the requirements for one's research.

The results of this dissertation also indicate that caution is warranted in conducting **(myopia) epidemiology research with (online) questionnaires**. The comparison of data from Study 1 and Study 3 demonstrated that even when assessing rather straightforward health topics such as having spectacles and reasons thereof, questionnaire data seems to be biased compared to direct measurements. Still, questionnaires could be a useful, cost-effective tool for monitoring prevalence development or the assessment of relations within the questionnaire data. Overall, more research regarding the feasibility of (online) epidemiological questionnaire studies is needed. In terms of myopia, it would be helpful to

further assess the comparability between (online) questionnaires and direct measurements of refractive status. One might, for example, (a) recruit parents from several schools for a spectacle ownership questionnaire about their children, and (b) subsequently perform refractive measurements on the children whose parents were asked to complete the questionnaire. Again, the refractive measurements would best be performed in a way that renders active parental consent unnecessary to keep participation biases as low as possible. Importantly, this procedure only enables the quantification of prevalence estimate differences between refractive measurements and questionnaires within the same group of (potential) participants. As previously described, different ways of (online) recruitment within an unknown population may include further biases that cannot be measured in this manner. However, the described approach enables quantification of potential differences between (a) questionnaire- and (b) directly measured prevalence rates.

When **using light meters to investigate light-myopia associations**, it is important to consider and carefully report methodological aspects regarding both the utilized devices and overall research methodology. This dissertation demonstrates partly substantial differences between the light meters themselves (Study 4 – Hönekopp & Weigelt, 2023) as well as their lux measurements and indoor-outdoor distinctions in an exemplary field setting (Study 5) – with respective lux measurement differences also having recently been found on a larger scale for three of the devices investigated here (Phan, 2022). As the presented findings are not conclusive, further investigation is needed. Study 5 for example indicates that, for some devices, it may be helpful to determine an own lux cut-off from measurements under similar conditions as the actual data acquisition for accurate indoor-outdoor distinction instead of using the common 1,000 lux cut-off. As the results from Study 5 are of a rather preliminary nature, further research is needed to e.g. assess for which devices and circumstances this procedure would, in fact, be (most) helpful. On a more general note, more research is also necessary to further uncover aspects of light-myopia associations – for example regarding the exact age range during which light exposure is especially important to prevent myopia (or potentially slow down progression), the potential impact of season on the strength or even presence of light-myopia associations, or the impact of a population's overall (bright) light exposure on the investigation of light-myopia associations.

Lastly, this dissertation also assessed the **feasibility of using a custom-made device for light-myopia research**. Overall, as a number of light meters with varying features are already commercially available for said research field – with likely more to come in the near future –, it is probably more practical to utilize one such device instead of developing one. This is especially the case because when using commercially available devices, one may avoid (potential) mechanical and device handling issues that need further time and resources before a – technically already functional – custom-made device can be used reliably in field research. However, Study 6 demonstrated that custom-made devices developed with

reasonable resources can exhibit an adequate and even good performance regarding both data acquisition (parameters) and data analysis procedures. Thus, one might consider this avenue especially if there are few or no (commercially) available options in one's field of research, or if one is in need of a very specific (combination) of measurements for one's research that none of the available devices offer.

4.4. Conclusion

This dissertation shed light on multiple important aspects of myopia research, such as myopia prevalence, uncorrected myopia, (online) epidemiological research methodology and the current state of light-myopia research both in terms of (available) devices and research methodology. As summarized above, multiple implications for both practice and future research avenues can be drawn from the results of this dissertation. I want to conclude by again stressing the points that are – in my opinion – most important moving forward.

In terms of light-myopia research, between-study differences in results may (partly) stem from differences in both study methodology and light meter specifications. Especially the comparability of measurements conducted with different light meters (and under different circumstances) should not generally be assumed, but investigated further. In conducting light-myopia research with light meters, careful consideration should be given to device selection, and one should be aware of the limitations of between-study comparability.

With regard to public health, more refractive error screenings should be conducted. When implemented at school, for example, such screenings could even be achieved at a relatively low expense while at the same time being a major step towards reducing the prevalence of uncorrected myopia along with the wide range of potential negative consequences the latter may entail. The high rates of uncorrected myopia in children and adolescents – found both in this dissertation and elsewhere – call into question the low priority that the German health system currently assigns to visual health assessments once school age has been reached.

By addressing these and other critical aspects, this dissertation not only provides valuable insights into myopia prevalence and research methodology, but also lays a foundation for more effective public health measures aimed at mitigating the impact of myopia.

5. Appendices

A. Supplementary Material to Study 1

Part A: Device A09 Data Transformation

In the following, we present results on the data preparation and A09 device data transformation based on the comparison study.

Supplementary Table A1

Comparison Study SER Measurements

device	*M*	*SD*
	right eye	
A09	-0.53D	1.14D
A12R-1	-0.80D	1.33D
A12R-2	-0.82D	1.24D
	left eye	
A09	-0.50D	1.47D
A12R-1	-0.71D	1.37D
A12R-2	-0.75D	1.25D

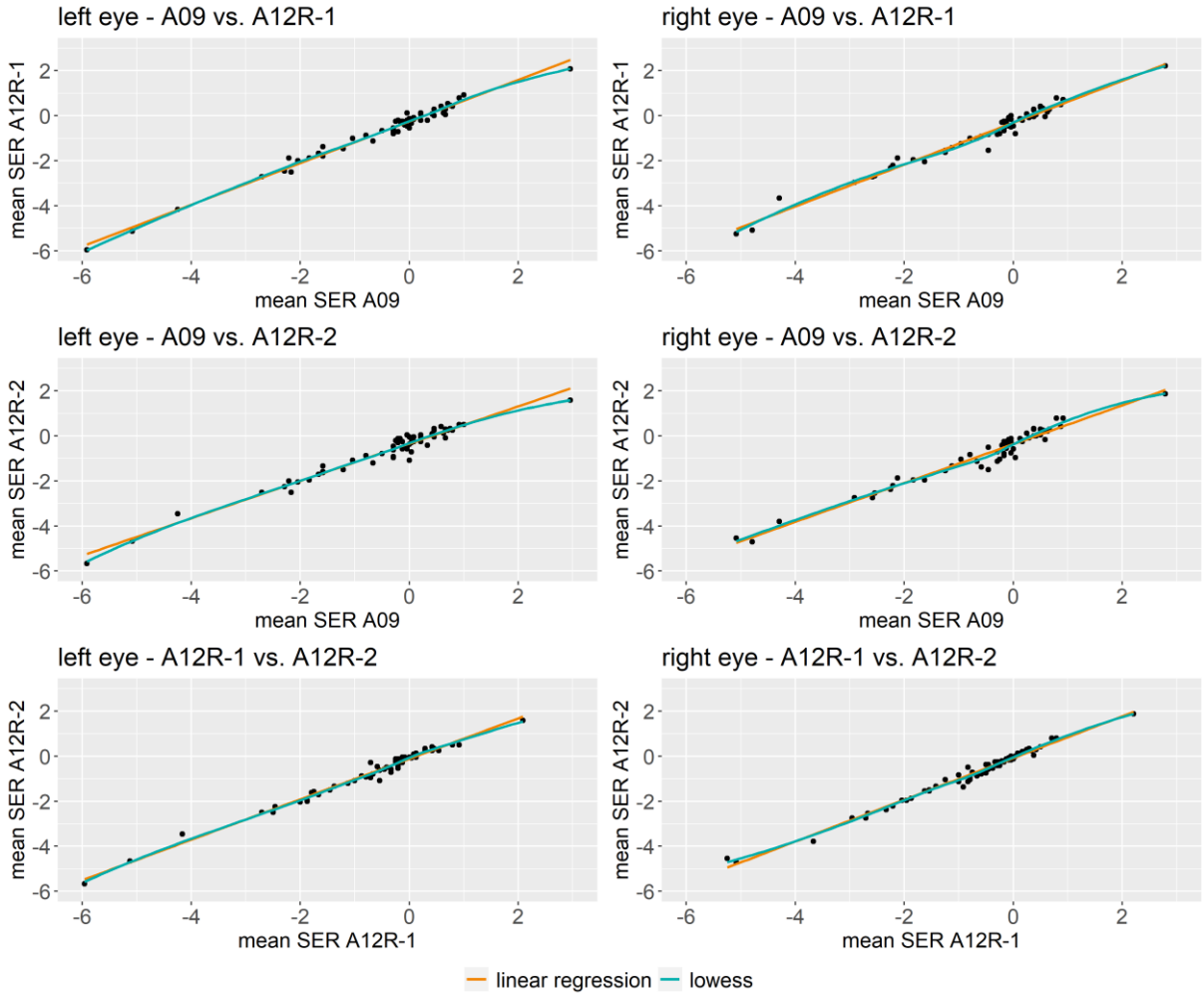
Note. Data from 58 participants.

Supplementary Table A2

T-test Results Comparing Devices' SER Measurements in Comparison Study

devices	*t*	*df*	95% CI	*p*
		right eye		
A09 vs. A12R-1	8.20	57	[0.20, 0.34]	< .001
A09 vs. A12R-2	6.78	57	[0.20, 0.38]	< .001
A12R-1 vs. A12R-2	0.84	57	[-0.03, 0.07]	.404
		left eye		
A09 vs. A12R-1	7.46	57	[0.16, 0.27]	< .001
A09 vs. A12R-2	5.47	57	[0.16, 0.35]	< .001
A12R-1 vs. A12R-2	1.50	57	[-0.01, 0.10]	.278

Note. CI = confidence interval. Holm-corrected p-values are reported.



Supplementary Figure A1. Linear regression and LOWESS lines for the mean SER data for each device pair in the comparison study.

Supplementary Table A3

GAMs With GCV to Predict Either A12R Mean SER From A09 Mean SER

A12R-1					
right eye					
component	**term**	**estimate**	**SE**	***t***	***p***
parametric coefficients	intercept	-0.22	0.09	-2.36	.022
	A09 mean SER	1.10	0.16	6.73	< .001
component	**term**	***edf***	**reference *df***	***F***	***p* (adjusted)**
smooth term	s(A09 mean SER)	4.00	8	1.03	.197
left eye					
component	**term**	**estimate**	**SE**	***t***	***p***
parametric coefficients	intercept	-0.25	0.03	-7.96	< .001
	A09 mean SER	0.92	0.04	21.12	< .001
component	**term**	***edf***	**reference *df***	***F***	***p* (adjusted)**
smooth term	s(A09 mean SER)	1.17	8	0.58	.086
A12R-2					
right eye					
component	**term**	**estimate**	**SE**	***t***	***p***
parametric coefficients	intercept	-0.40	0.08	-5.13	< .001
	A09 mean SER	0.79	0.13	6.00	< .001
component	**term**	***edf***	**reference *df***	***F***	***p* (adjusted)**
smooth term	s(A09 mean SER)	2.81	8	0.60	.197
left eye					
component	**term**	**estimate**	**SE**	***t***	***p***
parametric coefficients	intercept	-0.34	0.06	-5.27	< .001
	A09 mean SER	0.82	0.11	7.22	< .001
component	**term**	***edf***	**reference *df***	***F***	***p* (adjusted)**
smooth term	s(A09 mean SER)	2.75	8	0.80	.197

Note. GAM = generalized additive model. GCV = generalized cross-validation. SE = standard error. The models were fitted as described in the Methods section of the article. P-Values marked with "adjusted" are Holm-corrected due to multiple testing of four smooth terms.

Supplementary Table A4

GAMs With REML Criterion to Predict Either A12R Mean SER From A09 Mean SER

A12R-1					
right eye					
component	**term**	**estimate**	**SE**	***t***	***p***
parametric coefficients	intercept	-0.31	0.03	-9.42	< .001
	A09 mean SER	0.93	0.02	42.70	< .001
component	**term**	***edf***	**reference *df***	***F***	***p* (adjusted)**
smooth term	s(A09 mean SER)	0.00	8	0.00	.599
left eye					
component	**term**	**estimate**	**SE**	***t***	***p***
parametric coefficients	intercept	-0.26	0.04	-7.55	< .001
	A09 mean SER	0.91	0.05	18.66	< .001
component	**term**	***edf***	**reference *df***	***F***	***p* (adjusted)**
smooth term	s(A09 mean SER)	1.39	8	0.65	.093
A12R-2					
right eye					
component	**term**	**estimate**	**SE**	***t***	***p***
parametric coefficients	intercept	-0.36	0.04	-9.34	< .001
	A09 mean SER	0.86	0.03	25.41	< .001
component	**term**	***edf***	**reference *df***	***F***	***p* (adjusted)**
smooth term	s(A09 mean SER)	0.26	8	0.04	.586
left eye					
component	**term**	**estimate**	**SE**	***t***	***P***
parametric coefficients	intercept	-0.35	0.05	-7.77	< .001
	A09 mean SER	0.81	0.06	12.84	< .001
component	**term**	***edf***	**reference *df***	***F***	***p* (adjusted)**
smooth term	s(A09 mean SER)	1.30	8	0.42	.208

Note. GAM = Generalized additive model. GCV = Generalized cross-validation. SE = standard error. The models were fitted as described in the Methods section of the article. P-values marked with "adjusted" are Holm-corrected due to multiple testing of four smooth terms.

Supplementary Table A5

Linear Regressions to Predict A12R-1 and A12R-2 Mean SER From A09 Mean SER

coefficient	*B*	95% CI	SE	*t*	*p*
		right eye			
intercept	-0.3346365	[-0.40, -0.27]	0.03	-10.12	< .001
A09 mean SER	0.8961972	[0.85, 0.94]	0.02	40.52	< .001
		left eye			
intercept	-0.2957028	[-0.35, -0.24]	0.03	-10.38	< .001
A09 mean SER	0.8757312	[0.84, 0.91]	0.02	47.49	< .001

Note. SE = standard error. The mean SER of the A12R devices was averaged. For reasons of reproducibility, the linear transformation is reported as accurately as possible with seven decimal places of the point estimate. The formula *-0.3346365 + 0.8961972*A09 mean SER* was used for linear transformation of the A09 mean SER data for the right eye, and the formula *-0.2957028 + 0.8757312*A09 mean SER* for the left eye.

Part B: Recalculated Results

In the following, we present the results recalculated (1) for the complete data without linear transformation of the A09 device data (Supplementary Tables A6, A8, A10, A12, A14, A16, A18, A20 and A22, Supplementary Information A1 and A3) and (2) for the A12R devices' data only (Supplementary Tables A7, A9, A11, A13, A15, A17, A19, A21 and A23, Supplementary Information A2 and A4).

Supplementary Table A6

Myopia and High Myopia Prevalence in S1 and S2 Overall and by Grade for the Complete Data Without Linear Transformation of the A09 Device Data

	myopia				high myopia
sample	**age *M*(*SD*)**	***N***	**% ≤ -0.75D**	**% ≤ -0.5D**	**% ≤ -6.0D**
S1	9.30 (0.78)	488	8.4	10.7	0.4
grade 3	8.85 (0.73)	245	8.2	10.3	0.4
grade 4	9.75 (0.53)	243	8.6	11.1	0.4
S2	14.99 (1.12)	1,030	18.4	24.7	0.8
grade 8	13.98 (0.77)	346	10.1	16.2	0.2
grade 9	15.04 (0.80)	349	21.0	25.5	0.5
grade 10	15.97 (0.73)	335	24.5	32.8	1.5

Note. Age and *N* are presented for the sample included in the myopia prevalence calculation. For the high myopia prevalence calculation, 2 (10) of these participants were excluded from S1 (S2) as described in the Data Analysis section of the manuscript. Thus, 486 participants (age: 9.29±0. years) were included in the high myopia prevalence calculation for S1, as were 1020 participants (age: 14.98±1.12 years) for S2. The corresponding data are presented in Table 2.1 in the manuscript. Here, the prevalence for the ≤ -0.5D myopia cut-off in grades 9 & 10 is a bit lower than in the manuscript's data, but the general tendencies are similar.

Supplementary Table A7

Myopia and High Myopia Prevalence in S1 and S2 Overall and by Grade for the A12R Devices' Data Only

		myopia			high myopia
sample	**age *M*(*SD*)**	***N***	**% ≤ -0.75D**	**% ≤ -0.5D**	**% ≤ -6.0D**
S1	9.29 (0.75)	342	8.2	11.4	0.2
grade 3	8.85 (0.70)	165	7.9	10.9	0.6
grade 4	9.71 (0.51)	177	8.5	11.9	0.0
S2	15.03 (1.14)	677	20.8	28.8	0.7
grade 8	14.02 (0.82)	225	11.6	18.7	0.0
grade 9	15.08 (0.83)	230	22.6	28.7	0.5
grade 10	16.01 (0.75)	222	28.4	39.2	1.8

Note. Age and *N* are presented for the sample included in the myopia prevalence calculation. For the high myopia prevalence calculation, 1 (7) of these participants were excluded from S1 (S2) as described in the Data Analysis section of the manuscript. Thus, 341 participants (age: 9.29±0.74 years) were included in the high myopia prevalence calculation for S1, as were 670 participants (age: 15.03±1.14 years) for S2. The corresponding data are presented in Table 2.1 in the manuscript.

Supplementary Table A8

Myopia Prevalence in S1 and S2 by Gender for the Complete Data Without Linear Transformation of the A09 Device Data

	myopia				high myopia
sample	**age *M*(*SD*)**	***N***	**% ≤ -0.75D**	**% ≤ -0.5D**	**% ≤ -6.0D**
S1					
female	9.27 (0.77)	219	9.6	11.0	0.0
male	9.33 (0.79)	266	7.5	10.5	0.8
S2					
female	14.90 (1.05)	454	23.6	28.9	0.7
male	15.05 (1.17)	571	14.0	21.2	0.9

Note. Four participants with no information on their gender and four non-binary participants were excluded from these calculations. Age and *N* are presented for the sample included in the myopia prevalence calculation. For the high myopia prevalence calculation, 2 (10) of these participants were excluded from S1 (S2) as described in the Data Analysis section of the manuscript. Thus, 483 participants (age: 9.30±0.78 years) were included in the high myopia prevalence calculation for S1, as were 1015 participants (age: 14.98±1.12 years) for S2. The corresponding data are presented in Table 2.2 in the manuscript. Here, the prevalence for the ≤ -0.5D myopia cut-off in S2 is a bit lower than in the manuscript's data, but the general tendencies are similar.

Supplementary Table A9

Myopia Prevalence in S1 and S2 by Gender for the A12R Devices' Data Only

		myopia			high myopia
sample	**age *M*(*SD*)**	***N***	**% ≤ -0.75D**	**% ≤ -0.5D**	**% ≤ -6.0D**
S1					
female	9.32 (0.77)	154	10.4	12.3	0.0
male	9.28 (0.73)	186	6.5	10.7	0.5
S2					
female	14.92 (1.10)	294	26.9	33.0	0.7
male	15.12 (1.17)	381	16.0	25.5	0.8

Note. Two participants with no information on their gender and two non-binary participants were excluded from these calculations. Age and *N* are presented for the sample included in the myopia prevalence calculation. For the high myopia prevalence calculation, 1 (7) of these participants were excluded from S1 (S2) as described in the Data Analysis section of the manuscript. Thus, 339 participants (age: 9.29±0.74 years) were included in the high myopia prevalence calculation for S1, as were 668 participants (age: 15.03±1.14 years) for S2. The corresponding data are presented in Table 2.2 in the manuscript.

Supplementary Table A10

Myopia Prevalence and Standard Error per Gender by Grade for the Complete Data Without Linear Transformation of the A09 Device Data

	myopia (% ≤ -0.75D) (SE)		
sample	**female**	**male**	**all genders**
S1			
grade 3	7.3 (2.5)	9.0 (2.5)	8.2 (1.8)
grade 4	11.9 (3.1)	6.1 (2.1)	8.6 (1.8)
S2			
grade 8	11.9 (2.7)	8.9 (2.0)	10.1 (1.6)
grade 9	24.4 (3.3)	17.8 (2.9)	21.0 (2.2)
grade 10	34.3 (4.0)	15.9 (2.7)	24.5 (2.4)

Note. SE = standard error. The data for all genders include eight more participants than the data of males and females combined due to four non-binary participants and four participants with unknown gender. The corresponding data are presented in Figure 2.1 in the manuscript.

Supplementary Table A11

Myopia Prevalence and Standard Error per Gender by Grade for the A12R Devices' Data Only

	myopia (% ≤ -0.75D) (SE)		
sample	**female**	**male**	**all genders**
S1			
grade 3	7.0 (3.1)	8.6 (2.9)	7.9 (2.1)
grade 4	13.3 (3.7)	4.3 (2.1)	8.5 (2.1)
S2			
grade 8	14.9 (3.7)	9.2 (2.5)	11.6 (2.1)
grade 9	28.8 (4.5)	17.5 (3.4)	22.6 (2.8)
grade 10	36.5 (4.9)	21.6 (3.7)	28.4 (3.0)

Note. SE = standard error. The data for all genders include four more participants than the data of males and females combined due to two non-binary participants and two participants with unknown gender. The corresponding data are presented in Figure 2.1 in the manuscript. Here, the prevalence for female participants in grade 9 and for male participants in grade 10 is slightly higher in the manuscript's data, and the latter is also higher than that of male participants in grade 9 (other than in the manuscript's data) – however, the general tendencies are similar.

Supplementary Table A12

Myopia Prevalence in S2 by School for the Complete Data Without Linear Transformation of the A09 Device Data

	myopia				high myopia
sample	**age *M*(*SD*)**	***N***	**% ≤ -0.75D**	**% ≤ -0.5D**	**% ≤ -6.0D**
GSS	15.61 (1.14)	218	15.1	19.3	1.3
ISS	14.93 (1.03)	308	18.1	25.6	0.3
CS	14.71 (1.05)	287	20.9	28.9	0.3
GS	14.82 (1.06)	217	18.9	23.5	1.4

Note. Age and *N* are presented for the sample included in the myopia prevalence calculation. For the high myopia prevalence calculation, 10 participants were excluded as described in the Data Analysis section of the manuscript. The age of participants included in the high myopia calculation was comparable to those included in the myopia calculation (see Supplementary Table A1). GSS = general secondary school, ISS = intermediate secondary school, CS = comprehensive school, GS = grammar school. The corresponding data are presented in Table 2.3 in the manuscript. Here, the prevalence rates for the ≤ -0.5D cut-off are somewhat lower than in the manuscript's data, but the general tendencies are similar.

Supplementary Table A13

Myopia Prevalence in S2 by School for the A12R Devices' Data Only

	myopia				high myopia
sample	**age *M*(*SD*)**	***N***	**% ≤ -0.75D**	**% ≤ -0.5D**	**% ≤ -6.0D**
GSS	15.72 (1.15)	146	17.1	21.9	1.3
ISS	14.95 (1.06)	203	18.7	28.6	0.0
CS	14.69 (1.04)	183	27.3	37.2	0.0
GS	14.88 (1.07)	145	19.3	25.5	2.1

Note. Age and *N* are presented for the sample included in the myopia prevalence calculation. For the high myopia prevalence calculation, 7 participants were excluded as described in the Data Analysis section of the manuscript. The age of participants included in the high myopia calculation was comparable to those included in the myopia calculation (see Supplementary Table A2). GSS = general secondary school, ISS = intermediate secondary school, CS = comprehensive school, GS = grammar school. The corresponding data are presented in Table 2.3 in the manuscript. Here, the prevalence for the CS is slightly higher than in the manuscript's data, but the general tendencies are similar.

Supplementary Table A14

Myopia Prevalence and Standard Error in S2 per School by Grade for the Complete Data Without Linear Transformation of the A09 Device Data

	myopia (% ≤ -0.75D) (SE)			
sample	**GSS**	**ISS**	**CS**	**GS**
grade 8	10.2 (3.5)	12.6 (3.4)	11.5 (3.1)	4.3 (2.5)
grade 9	15.6 (3.8)	22.1 (4.1)	24.4 (4.7)	21.7 (5.0)
grade 10	22.0 (5.9)	19.3 (3.8)	27.8 (4.6)	29.1 (5.1)

Note. SE = standard error. GSS = general secondary school, ISS = intermediate secondary school, CS = comprehensive school, GS = grammar school. The corresponding data presented in Figure 2.2 in the manuscript.

Supplementary Table A15

Myopia Prevalence and Standard Error in S2 per School by Grade for the A12R Devices' Data Only

	myopia (% ≤ -0.75D) (SE)			
sample	**GSS**	**ISS**	**CS**	**GS**
grade 8	9.8 (4.2)	15.6 (4.6)	15.2 (4.4)	2.3 (2.3)
grade 9	16.9 (4.9)	19.1 (4.8)	33.3 (6.3)	21.7 (6.1)
grade 10	27.8 (7.6)	21.1 (4.9)	35.0 (6.2)	30.9 (6.3)

Note. SE = standard error. GSS = general secondary school, ISS = intermediate secondary school, CS = comprehensive school, GS = grammar school. The corresponding data are presented in Figure 2.2 in the manuscript Here, grade 9 ISS participants have a minimally lower prevalence than grade 9 GS participants, other than in the manuscript's data. Also, the prevalence of CS participants in grades 9 & 10 is somewhat higher than in the manuscript's data, and other than in the manuscript's data, the prevalence of grade 10 CS participants is higher than that of grade 10 GS participants. Apart from that, the general tendencies are similar.

Supplementary Information A1: SER Analyses for the Complete Data Without Linear Transformation of the A09 Device Data

SER was significantly more myopic in the older (S2, N = 1,029) than the younger (S1, N = 486) sample for the complete data without linear transformation of the A09 device data ($t(1513) = -6.88$, $p < .001$, $d = 0.38$, 95% CI [-0.59, -0.33]; S1: $M = 0.19$D, SD = 1.11D; S2: $M = -0.26$D, $SD = 1.25$D).

In the younger sample (S1, N = 483), the regression model with the predictors grade and gender did not reach statistical significance ($R^2 = .005$, $F(2, 480) = 1.37$, $p = .255$). In the "all possible subsets" approach, the best-fitting model did not include any of the given predictors. From the models including predictors, the best-fitting model included grade as only predictor, and it did also not reach statistical significance ($R^2 = .005$, $F(1, 481) = 2.578$, $p = .109$).

In the older sample (S2, N = 1,015), both grade and gender were identified as significant predictors of SER (see Supplementary Table A18, model A), with the respective regression model being overall significant ($R^2 = .024$, $F(3, 1011) = 8.46$, $p < .001$). This model was also identified as the most promising one via the "all possible subsets" approach. The regression model including grade, gender and grade × gender as predictors (model B) exhibited the next-highest adjusted R^2 and was thus also fitted, despite a substantial BIC difference to model A. Model B also explained variance in SER ($R^2 = .029$, $F(5, 1009) = 6.01$, $p < .001$), but while grade (grade 9: $B = -0.31$, $p = .029$; grade 10: $B = -0.63$, $p < .001$) and the gender × grade term for grade 10 ($B = 0.38$, $p = .049$) significantly predicted SER in this model (the latter other than in the manuscript's data), gender and the gender × grade term for grade 9 did not reach significance ($B = 0.05$, $p = .799$). An F-test for nested models showed that model B did not fit the data better than model A ($F(2, 1011) = 2.29$, $p = .102$).

SER was more myopic in females than males in S2 (females: $M = -0.37$D, $SD = 1.26$D, males: $M = -0.18$D, $SD = 1.22$D). Post-hoc Holm-corrected Welch two sample t-tests showed that the SER of grade 9 ($M = -0.32$D, $SD = 1.29$D) and grade 10 ($M = -0.45$D, $SD = 1.34$D) participants was significantly more myopic than that of grade 8 participants ($M = -0.03$D, $SD = 1.06$D; grade 8 vs. 9: $t(662.52) = 3.16$, $p = .003$, $d = 0.24$, 95% CI [0.11, 0.46]; grade 8 vs. 10: $t(617.75) = 4.41$, $p < .001$, $d = 0.34$, 95% CI [0.23, 0.60]). There was no significant difference between the SER of grade 9 and 10 participants ($t(662.38) = 1.26$, $p = .209$, $d = 0.10$, 95% CI [-0.07, 0.33]).

Supplementary Information A2: SER Analyses for the A12R Devices' Data Only

SER was significantly more myopic in the older (S2, $N = 677$) than the younger (S1, $N = 341$) sample for the A12R devices' data only ($t(1,016) = -6.21$, $p < .001$, $d = 0.41$, 95% CI [-0.63, -0.32]; S1: $M = 0.14$D, $SD = 0.99$D; S2: $M = -0.33$D, $SD = 1.23$D).

In the younger sample (S1, $N = 339$), the regression model with the predictors grade and gender did not reach statistical significance ($R^2 = .031$, $F(2, 336) = 0.20$, $p = .822$). In the "all possible subsets" approach, the best-fitting model did not include any of the given predictors. From the models including predictors, the best-fitting model included grade as only predictor, and it did also not reach statistical significance ($R^2 = .001$, $F(1, 337) = 0.390$, $p = .533$).

In the older sample (S2, $N = 668$), both grade and gender were identified as significant predictors of SER (see Supplementary Table A19, model A), with the respective regression model being overall significant ($R^2 = .032$, $F(3, 664) = 7.27$, $p < .001$). This model was also identified as the most promising one via the "all possible subsets" approach. The regression model including grade, gender and grade × gender as predictors (model B) exhibited a slightly higher adjusted R^2 and was thus also fitted, despite a substantial BIC difference to model A. Furthermore, and other than in the manuscript's data, the model with age, gender, grade and age × gender as predictors performed (almost) equally in the "all possible subsets" approach as model B for these data – though fitting a model with both age and grade included may presumably be problematic regarding multicollinearity, since these two variables are highly correlated S2 (Spearman's rho; $r_s = .76$). Model B also explained variance in SER ($R^2 = .033$, $F(5, 662) = 4.50$, $p < .001$), but while grade 10 ($B = -0.58$, $p = .001$) significantly predicted SER in this model, the other predictors did not (grade 9: $B = -1.91$, $p = .057$; grade (9) × gender: $B = 0.18$, $p = .445$; grade (10) × gender: $B = 0.17$, $p = .465$; unlike here, grade 9 also significantly predicted SER in model B in the manuscript's data). An F-test for nested models showed that model B did not fit the data better than model A ($F(2, 664) = 0.37$, $p = .689$).

SER was more myopic in females than males in S2 (females: $M = -0.45$D, $SD = 1.31$D, males: $M = -0.25$D, $SD = 1.15$D). Post-hoc Holm-corrected Welch two sample t-tests showed that the SER of grade 9 ($M = -0.33$D, $SD = 1.21$D) and grade 10 ($M = -0.58$D, $SD = 1.40$D) participants was significantly more myopic than that of grade 8 participants ($M = -0.10$D, $SD = 1.00$D; grade 8 vs. 9: $t(436.8) = 2.25$, $p = .049$, $d = 0.21$, 95% CI [0.03, 0.44]; grade 8 vs. 10: $t(388.14) = 4.16$, $p < .001$, $d = 0.40$, 95% CI [0.25, 0.71]). Furthermore, and other than in the manuscript's data, the SER of grade 10 participants was significantly more myopic than that of grade 9 participants ($t(425.81) = 1.99$, $p = .049$, $d = 0.19$, 95% CI [0.00, 0.49]).

Supplementary Table A16

Mean SER and Standard Error per Gender by Grade for the Complete Data Without Linear Transformation of the A09 Device Data

sample	female	male	all genders
S1			
grade 3	0.39D (0.10)	0.17D (0.09)	0.27D (0.09)
grade 4	0.03D (0.11)	0.17D (0.10)	0.11D (0.08)
S2			
grade 8	-0.06D (0.08)	-0.01D (0.08)	-0.03D (0.06)
grade 9	-0.37D (0.09)	-0.27D (0.10)	-0.32D (0.07)
grade 10	-0.69D (0.12)	-0.26D (0.09)	-0.45D (0.07)

Note. The data for all genders include eight more participants than the data of males and females combined due to four non-binary participants and four participants with unknown gender. The corresponding data are presented in Figure 2.3 in the manuscript. Here, the SER is slightly less myopic than in the manuscript's data, though the general tendencies are comparable.

Supplementary Table A17

Mean SER and Standard Error per Gender by Grade for the A12R Devices' Data Only

sample	female	male	all genders
S1			
grade 3	0.31D (0.12)	0.07D (0.10)	0.17D (0.08)
grade 4	-0.01D (0.13)	0.21D (0.08)	0.11D (0.08)
S2			
grade 8	-0.14D (0.11)	-0.06D (0.08)	-0.10D (0.07)
grade 9	-0.47D (0.12)	-0.22D (0.11)	-0.33D (0.08)
grade 10	-0.72D (0.16)	-0.47D (0.12)	-0.58D (0.10)

Note. The data for all genders include eight more participants than the data of males and females combined due to two non-binary participants and two participants with unknown gender. The corresponding data are presented in Figure 2.3 in the manuscript. Here, other than in the manuscript's data, male participants of grade 3 have a more myopic SER than male participants of grade 4, and the SER difference between male participants of grade 9 & 10 is somewhat larger than in the manuscript's data, due to the grade 9 prevalence being less, and the grade 10 prevalence being more myopic than in the manuscript's data. Other than that, the general tendencies are comparable.

Supplementary Table A18

Coefficient Estimates of Multiple Linear Regression Model A for S2 for the Complete Data Without Linear Transformation of the A09 Device Data

coefficient	*B*	95% CI	SE	*t*	*p*
intercept	-0.14	[-0.29, 0.02]	0.08	-1.74	.083
grade (9)	-0.27	[0.03, 0.34]	0.09	-2.91	.004
grade (10)	-0.41	[-0.46, -0.09]	0.10	-4.30	< .001
gender	0.18	[-0.60, -0.22]	0.08	2.35	.020

Note. CI = confidence interval, SE = standard error. The corresponding data are presented in Table 2.4 in the manuscript.

Supplementary Table A19

Coefficient Estimates of Multiple Linear Regression Model A for S2 for the A12R Devices' Data Only

coefficient	*B*	95% CI	SE	*t*	*p*
intercept	-0.21	[-0.40, -0.02]	0.10	-2.13	.033
grade (9)	-0.23	[-0.45, -0.01]	0.11	-2.02	.044
grade (10)	-0.48	[-0.71, -0.25]	0.12	-4.16	< .001
gender	0.19	[0.01, 0.38]	0.09	2.06	.040

Note. CI = confidence interval, SE = standard error. The corresponding data are presented in Table 2.4 in the manuscript.

Supplementary Table A20

Prevalence of Uncorrected Myopia in S1 and S2 Overall and by Grade for the Complete Data Without Linear Transformation of the A09 Device Data

	myopia cut-off SER ≤ -0.75D		myopia cut-off SER ≤ -1D	
sample	***N***	**% uncorrected**	***N***	**% uncorrected**
S1	41	51.5	39	48.7
grade 3	20	55.0	18	47.6
grade 4	21	50.0	21	47.6
S2	190	40.5	154	31.8
grade 8	35	42.9	27	33.3
grade 9	73	37.0	59	30.5
grade 10	82	42.7	68	32.4

Note. N indicates the number of myopic participants per the respective cut-off. The given prevalence indicates the percentage of myopic participants without visual aid based on all myopic participants. The corresponding data are presented in Table 2.5 in the manuscript. Here, the prevalence of uncorrected myopia for grade 8 is somewhat lower than in the manuscript's data, but the general tendencies are similar.

Supplementary Table A21

Prevalence of Uncorrected Myopia in S1 and S2 Overall and by Grade for the A12R Devices' Data Only

	myopia cut-off SER ≤ -0.75D		myopia cut-off SER ≤ -1D	
sample	***N***	**% uncorrected**	***N***	**% uncorrected**
S1	28	57.1	26	52.8
grade 3	13	61.5	11	54.5
grade 4	15	53.3	15	53.3
S2	141	43.3	110	32.7
grade 8	26	42.3	20	35.0
grade 9	52	44.2	40	35.0
grade 10	63	42.9	50	30.0

Note. N indicates the number of myopic participants per the respective cut-off. The given prevalence indicates the percentage of myopic participants without visual aid based on all myopic participants. The corresponding data are presented in Table 2.5 in the manuscript. Here, the prevalence of uncorrected myopia for S1 as well as grade 9 is somewhat higher than in the manuscript's data, while that of grade 8 for the ≤ -0.75D cut-off is somewhat lower. However, the general tendencies are comparable.

Supplementary Table A22

Prevalence of Corrected and Uncorrected Myopia and Standard Error by Grade Relative to the Overall Sample for the Complete Data Without Linear Transformation of the A09 Device Data

	myopia cut-off SER ≤ -0.75D	
sample	**% uncorrected (SE)**	**% corrected (SE)**
S1		
grade 3	4.5 (1.3)	3.7 (1.2)
grade 4	4.1 (1.3)	4.5 (1.3)
S2		
grade 8	4.3 (1.1)	5.8 (1.3)
grade 9	7.7 (1.4)	13.2 (1.8)
grade 10	10.4 (1.7)	14.0 (1.9)

Note. SE = standard error. The corresponding data are presented in Figure 2.4 in the manuscript.

Supplementary Table A23

Prevalence of Corrected and Uncorrected Myopia and Standard Error by Grade Relative to the Overall Sample for the A12R Devices' Data Only

	myopia cut-off SER ≤ -0.75D	
sample	**% uncorrected (SE)**	**% corrected (SE)**
S1		
grade 3	4.8 (1.7)	3.0 (1.3)
grade 4	4.5 (1.6)	4.0 (1.5)
S2		
grade 8	4.9 (1.4)	6.7 (1.7)
grade 9	10.0 (2.0)	12.6 (2.2)
grade 10	12.1 (2.2)	16.2 (2.5)

Note. SE = standard error. The corresponding data are presented in Figure 2.4 in the manuscript.

Supplementary Information A3: Further Uncorrected Myopia Data for the Complete Data Without Linear Transformation of the A09 Device Data

The prevalence of uncorrected myopia for the complete data without linear transformation of the A09 device data was 55.0% for males and 47.6% for females in the younger sample (S1), and 42.5% for males and 39.3% for females in the older sample (S2). With the SER ≤ -1D myopia cut-off, these numbers were 52.6% (28.6%) for males and 45.0% (34.1%) for females in S1 (S2).

Of the myopic participants in the younger sample (S1), 38.9% (7 of 18 children) in the three schools with the lowest social index levels – i.e., lower social burden –, and 60.9% (14 of 23 children) in the three schools with the highest social index levels had uncorrected myopia. It is, however, important to consider that data on (un)corrected myopia in S1 is based on 41 myopic participants only.

Supplementary Information A4: Further Uncorrected Myopia Data for the A12R Devices' Data Only

The prevalence of uncorrected myopia for the A12R devices' data only was 66.7% for males (this being somewhat higher than in the manuscript's data) and 50.0% for females in the younger sample (S1), and 44.3% for males and 43.0% for females in the older sample (S2). With the SER ≤ -1D myopia cut-off, these numbers were 63.6% (28.3%) for males and 46.7% (36.5%) for females in S1 (S2), with the prevalence for males in S1 again somewhat higher than in the manuscript's data.

Of the myopic participants in the younger sample (S1), 45.5% (5 of 11 children) in the three schools with the lowest social index levels – i.e., lower social burden –, and 64.7% (11 of 17 children) in the three schools with the highest social index levels had uncorrected myopia. It is, however, important to consider that data on (un)corrected myopia in S1 is based on 28 myopic participants only.

Part C: Detailed Statistical Parameters

In the following, we present the statistical parameters of the analyses we performed with regard to SER associations that are not reported on in detail in the manuscript.

Supplementary Information A5: Detailed Statistical Parameters of the Calculations Regarding SER Associations

SER was significantly more myopic in S2 (N = 1,029) than S1 (N = 486; t(1,513) = -7.17, p < .001, d = 0.39, 95% CI [-0.58, -0.33]; S1: M = 0.08D, SD = 1.06D; S2: M = -0.37D, SD = 1.20D).

For S1, the regression model with the predictors grade and gender did not reach statistical significance (R^2 = .004, F(2, 480) = 0.99, p = .371). The model with only grade as predictor did also not reach statistical significance (R^2 = .004, F(1, 481) = 1.84, p = .175).

For S2, the regression model with grade and gender as predictors (model A) was overall significant (R^2 = .025, F(3, 1,011) = 8.59, p < .001), as were both predictors (grade 9: B = -0.26, p = .005; grade 10: B = -0.40, p < .001; gender: B = 0.18, p = .015). The regression model with grade, gender, and grade × gender as predictors (model B) was overall significant (R^2 = .029, F(5, 1009) = 5.96, p < .001), but only grade was a significant predictor (grade 9: B = -0.31, p = .023; grade 10: B = -0.60, p < .001), and gender as well as both gender × grade terms were not significant (gender: B = 0.04, p = .750; grade (9) × gender: B = 0.08, p = .643; grade (10) × gender: B = 0.35, p = .057). An F-test for nested models (F(2, 1011) = 1.97, p = .139) showed that model B did not fit the data better than model A.

Post-hoc, Holm-corrected Welch two-sample t-tests showed that the SER of grade 9 and grade 10 participants was significantly more myopic than that of grade 8 participants (grade 8 vs. 9: t(661.23) = 3.09, p = .004, d = 0.24, 95% CI [0.10, 0.44]; grade 8 vs. 10: t(615.36) = 4.42, p < .001, d = 0.34, 95% CI [0.22, 0.58]). The SER was not significantly different between grade 9 and 10 participants (t(662.08) = 1.33, p = .183, d = 0.10, 95% CI [-0.06, 0.32]).

Part D: Results of the "All Possible Subsets" Analyses

In the following, we present the results of the "all possible subsets" analyses on regression models for the SER data.

Supplementary Table A24

„All Possible Subsets" Regression Output for the Younger Sample (S1)

intercept	age	gender	grade	age × gender	age × grade	gender × grade	age × gender × grade	adjusted R^2	BIC	delta
0.082	NA	NA	NA	NA	NA	NA	NA	0.000	1,441.756	0.000
0.147	NA	NA	+	NA	NA	NA	NA	0.004	1,446.090	4.334
0.102	NA	+	NA	NA	NA	NA	NA	0.000	1,447.789	6.034
0.254	0.000	NA	NA	NA	NA	NA	NA	0.000	1,447.848	6.092
-0.270	0.000	NA	+	NA	NA	NA	NA	0.005	1,451.893	10.137
0.167	NA	+	+	NA	NA	NA	NA	0.004	1,452.121	10.365
0.266	0.000	+	NA	NA	NA	NA	NA	0.000	1,453.889	12.133
0.254	NA	+	+	NA	NA	+	NA	0.010	1,455.580	13.824
1.478	0.000	+	NA	+	NA	NA	NA	0.008	1,456.540	14.784
0.263	0.000	NA	+	NA	+	NA	NA	0.007	1,456.899	15.143
-0.260	0.000	+	+	NA	NA	NA	NA	0.005	1,457.903	16.147
0.931	0.000	+	+	+	NA	NA	NA	0.012	1,461.028	19.272
-0.267	0.000	+	+	NA	NA	+	NA	0.012	1,461.160	19.404
0.259	0.000	+	+	NA	+	NA	NA	0.008	1,462.969	21.213
1.524	0.000	+	+	+	+	NA	NA	0.015	1,465.910	24.154
0.237	0.000	+	+	NA	+	+	NA	0.014	1,466.279	24.523
0.501	0.000	+	+	+	NA	+	NA	0.013	1,466.545	24.789
1.105	0.000	+	+	+	+	+	NA	0.016	1,471.524	29.768
1.101	0.000	+	+	+	+	+	+	0.016	1,477.704	35.948

Note. Some values in the column "age" are zero due to rounding – they are not actually zero. "delta" refers to the difference in BIC.

Supplementary Table A25

„All Possible Subsets" Regression Output for the Older Sample (S2)

intercept	age	gender	grade	age × gender	age × grade	gender × grade	age × gender × grade	adjusted R^2	BIC	delta
-0.153	NA	NA	+	NA	NA	NA	NA	0.020	3,254.179	0.000
-0.260	NA	+	+	NA	NA	NA	NA	0.026	3,255.134	0.955
1.104	0.000	+	NA	NA	NA	NA	NA	0.017	3,257.307	3.129
1.124	0.000	NA	NA	NA	NA	NA	NA	0.009	3,257.949	3.770
2.403	-0.001	+	NA	+	NA	NA	NA	0.021	3,259.900	5.722
-0.372	NA	NA	NA	NA	NA	NA	NA	0.000	3,259.919	5.740
-0.478	NA	+	NA	NA	NA	NA	NA	0.007	3,260.473	6.295
-0.334	0.000	NA	+	NA	NA	NA	NA	0.020	3,261.030	6.851
-0.246	0.000	+	+	NA	NA	NA	NA	0.026	3,262.056	7.877
-0.177	NA	+	+	NA	NA	+	NA	0.030	3,265.015	10.836
0.980	0.000	+	+	+	NA	NA	NA	0.029	3,265.577	11.398
-0.180	0.000	+	+	NA	NA	+	NA	0.030	3,271.938	17.759
-1.280	0.000	NA	+	NA	+	NA	NA	0.021	3,273.818	19.639
-1.189	0.000	+	+	NA	+	NA	NA	0.027	3,274.837	20.659
0.448	0.000	+	+	+	NA	+	NA	0.030	3,278.417	24.238
0.078	0.000	+	+	+	+	NA	NA	0.030	3,278.525	24.346
-1.267	0.000	+	+	NA	+	+	NA	0.031	3,284.409	30.231
-0.742	0.000	+	+	+	+	+	NA	0.031	3,291.115	36.936
-1.956	0.000	+	+	+	+	+	+	0.032	3,304.360	50.181

Note. Some values in the column "age" are zero due to rounding – they are not actually zero. "delta" refers to the difference in BIC.

B. Supplementary Material to Study 3

Supplementary Table B1

Prevalence (Standard Error) of Spectacles per Recruitment Strategy and Age Group

	age group						
strategy	**all ages**	**0-2 years**	**3-5 years**	**6-8 years**	**9-11 years**	**12-14 years**	**15-17 years**
CLUSTER	19.7 (2.2)	5.4 (3.8)	9.8 (3.1)	16.0 (3.8)	28.3 (6.7)	39.6 (7.1)	39.1 (10.4)
KSW	29.3 (3.9)	4.3 (4.3)	26.5 (7.7)	34.4 (8.5)	29.2 (9.5)	50.0 (12.1)	44.4 (17.6)
NETWORK	23.5 (1.5)	1.8 (1.8)	6.7 (2.6)	15.6 (3.5)	18.1 (3.1)	33.3 (3.1)	36.0 (3.7)
TARGET	14.9 (2.4)	2.8 (2.8)	15.4 (5.9)	15.2 (5.4)	9.7 (5.4)	24.2 (7.6)	23.3 (7.9)
WILD	23.4 (2.8)	1.6 (1.6)	8.0 (3.9)	35.9 (7.8)	40.0 (8.4)	35.7 (9.2)	73.3 (11.8)

Supplementary Table B2

Prevalence (Standard Error) of Spectacles Due to Myopia per Recruitment Strategy and Age Group

	age group						
strategy	**all ages**	**0-2 years**	**3-5 years**	**6-8 years**	**9-11 years**	**12-14 years**	**15-17 years**
CLUSTER	8.8 (1.5)	0.0 (0.0)	1.1 (1.1)	7.4 (2.7)	13.0 (5.0)	22.9 (6.1)	21.7 (8.8)
KSW	12.1 (2.8)	0.0 (0.0)	8.8 (4.9)	9.4 (5.3)	8.3 (5.8)	33.3 (11.4)	33.3 (16.7)
NETWORK	13.5 (1.2)	1.8 (1.8)	2.2 (1.6)	2.8 (1.6)	9.1 (2.2)	20.2 (2.7)	25.6 (3.3)
TARGET	7.4 (1.8)	0.0 (0.0)	5.1 (3.6)	4.3 (3.0)	0.0 (0.0)	15.2 (6.3)	23.3 (7.9)
WILD	12.1 (2.2)	0.0 (0.0)	0.0 (0.0)	12.8 (5.4)	20.0 (6.9)	32.1 (9.0)	46.7 (13.3)

C. Supplementary Material to Study 4

Supplementary Table C1

Keywords and Dates of the Conducted Abstract Searches

search term	dates of searching
PubMed searches	
myopi* AND light	2021/11/30, 2023/01/02 (2022 only)
myopi* AND light sensor	2021/12/14, 2023/01/02 (2022 only)
myopi* AND "light exposure"	2021/12/14, 2023/01/02 (2022 only)
myopi* AND "light intensity"	2021/12/23, 2023/01/02 (2022 only)
myopi* AND "light level"	2021/12/23, 2023/01/02 (2022 only)
myopi* AND "light meter"	2021/12/23, 2023/01/02 (2022 only)
myopi* AND sunlight	2022/01/11, 2023/01/02 (2022 only)
myopi* AND "ambient illumina*"	2022/01/11, 2023/01/02 (2022 only)
myopi* AND lux	2022/01/11, 2023/01/02 (2022 only)
myopi* AND RGB	2022/01/25, 2023/01/02 (2022 only)
myopi* AND "circadian rhythm"	2022/01/25, 2023/01/02 (2022 only)
myopi* AND outdoor	2022/02/15, 2023/01/02 (2022 only)
myopi* AND wearable device	2022/02/22, 2023/01/02 (2022 only)
"refractive error" AND light sensor	2022/02/22, 2023/01/02 (2022 only)
"axial length" AND light sensor	2022/02/22, 2023/01/02 (2022 only)
Web of Science searches	
myopi* AND light	2022/05/13, 2023/01/02 (2022 only)

Supplementary Table C2

Identified Devices from Literature Search and Subsequent Search Items

device	searched for "… AND myopi*"	comment
Actigraph GT3X+	Actigraph GT3X+	
Actillume	Actillume	
Action W Actigraph Watch with Motion Logger-L	Action W Actigraph Watch with Motion Logger-L	
Actiwatch 2	Actiwatch 2	
Actiwatch-L	Actiwatch-L	
Actiwatch Spectrum	Actiwatch Spectrum	
Actiwatch Spectrum Plus	Actiwatch Spectrum Plus	
Actiwatch Spectrum PRO	Actiwatch Spectrum PRO	
AKESO	AKESO	identified later during "cited references search"
Clouclip / Clouclip M2	Clouclip	sometimes version (M2) specified, sometimes not
Daysimeter	Daysimeter	different names and versions found (Dimesimeter, Daysimeter-D, Daysimeter-S)
FitSight	FitSight	
GENEActive	GENEActive	
HOBO Pendant UA-002-08	HOBO	only differs from version UA-002-64 regarding storage capacity
HOBO Pendant UA-002-64	HOBO	only differs from version UA-002-08 regarding storage capacity
LuxBlick	LuxBlick	
Mumu	Mumu	
MyLyt	-	identified during final literature search in January 2023; thus, no keyword search for ([device name]) AND (myopi*) was conducted
Octagonal Sleep Watch-L	Octagonal Sleep Watch-L	
Sleepwatch-L	Sleepwatch-L	
StowAway	StowAway	
Vitalog PMS-8	Vitalog PMS-8	

Note. Included are all devices that were identified after the first part of the literature search, for which a search for ([device name]) AND (myopi*) was then conducted. This encompasses both devices that had been used in a myopia-related study before as well as devices that – based on our knowledge – had not, but may be used in one, based on their capacity to measure light intensity. The two devices (AKESO and MyLyt) identified later during the literature search are included as well.

Supplementary Information C1: Results of the Excluded Publications

Four publications were identified, in which primarily other aspects of light exposure and/or myopia were investigated, but the association between the two was also considered, the results of which will be presented here. Abbott et al. (2018) investigated the relationship between intrinsically photosensitive retinal ganglion cell (ipRGC)-driven pupil response and light exposure, also examining relationships between light exposure, sleep, and melatonin in emmetropic and myopic adults. No significant differences were detected between refractive groups regarding time outdoors (> 1,000 lux) or white light exposure, measured with Actiwatch Spectrum. Ostrin (2018) evaluated the ipRGC-driven pupil response in children and examined it with Actiwatch Spectrum-measured light exposure and refractive error, revealing similar average white light exposure over 24 hours between myopic and non-myopic participants. Burfield et al. (2019) examined ocular and systemic diurnal rhythms in emmetropic and myopic adults as well as relationships with light exposure measured with Actiwatch Spectrum. Time outdoors (≥ 1,000 lux) as well as white light exposure during the day and night were similar between myopic and emmetropic participants. Lastly, Flanagan et al. (2020) studied the relationship between refractive error, circadian phase, and melatonin in young adults, also considering prior light exposure measured with Actiwatch 2. Myopic participants were found to have spent more time in "indoor" photopic light (3 - ≤ 1,000 lux) than non-myopic participants, but time "indoors" was not correlated to either SER or axial length. Various other light parameters exhibited no refractive group differences. Another publication excluded from the review despite being closely related to its scope was by Fan et al. (2022), who longitudinally examined the effects of visual behavior in online versus traditional learning on myopia progression in children wearing the Akeso eye care glasses. They found a negative correlation between outdoor time and axial length growth. This was the only analysis on the association between light exposure and myopia, and outdoor time was classified by means of UV and lux data together. As there was no analysis on light intensities alone, the publication was not included. Finally, Tanrıverdi et al. (2019, April 28-May 2) presented a conference poster comparing percentages of different illumination conditions, measured with the Vivior Monitor, in progressive myopic children. They reported 15.5% time in > 50 lux, 61.3% in 10-50 lux, and 23.2% in < 10 lux. Since no analysis of light exposure data with regard to different refractive groups or refractive error was conducted, this publication was also not included.

Supplementary Table C3

Detailed Information About the Included Publications

publication	type of publication	general purpose of the study	kind of study	device[a]	device position & orientation[a]	logging interval[a]	place & time of light data acquisition
Backhouse et al. (2011)	conference poster	examination of school-aged children's light exposure patterns in relation to refractive error	observation - longitudinal	HOBO Pendant UA-002-64	*not reported*	10 s	place: *not reported* – probably Auckland, New Zealand (cf. affiliations) time: June, July, August (year: *not reported*) – one measurement period/month
Dharani et al. (2012)	journal article	comparison of outdoor activities diary & light meter to assess two possible myopia predictors – light exposure and outdoor time – in Singapore children	observation – cross-sectional; methodological	HOBO Pendant UA-002-64	worn on shirt with safety pin, light sensor facing outward	5 min	place: Singapore time: April-June 2011
Schmid et al. (2013)	journal article	exploration of the relationship between near work, indoor illumination, daily sunlight & UV exposure in emmetropic & myopic university students	observation – cross-sectional	HOBO Pendant UA-002-08	clipped on shirt pocket, collar, or midline in stable upright position & chain through eyelet at end cap	5 min	place: Brisbane, Queensland, Australia time: *not reported*
Alvarez and Wildsoet (2013)	journal article	report of a technique for quantifying light exposure with wearable sensors	observation – cross-sectional; methodological	HOBO Pendant UA-002-64	mounted on custom pedestal attached to Velcro armband worn on upper arm, light sensor pointing skyward	10 s	place: Northern California, USA time: March, 30-April, 13 2011 (spring season), November, 3-November, 17 2011 (fall season), February, 23-March, 8 2012 (winter season)
Read et al. (2014)	journal article	objective assessment of daily light exposure and physical activity in myopic & emmetropic children	observation – cross-sectional	Actiwatch 2	non-dominant wrist	30 s	place: Brisbane area, Australia time: July-December 2012

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Read et al. (2015)	journal article	examination of the relationship between objectively measured ambient light exposure and longitudinal changes in axial eye growth in children	observation – longitudinal	Actiwatch 2	non-dominant wrist	30 s	place: Brisbane area, Queensland, Australia time: July-December 2012 (1st measurement period) & February-August 2013 (2nd measurement period)
Ostrin (2017)	journal article	continuous light exposure & activity measurement across seasons & refractive error groups for assessment of objectively measured differences & comparison with subjective data	observation – cross-sectional	Actiwatch Spectrum	wrist	30 s	place: Houston, Texas, USA time: January-November 2014
Wu et al. (2018)	journal article	investigation of the effectiveness of a school-based program promoting outdoor activities for myopia prevention & identification of protective light intensities	intervention; observation – longitudinal	HOBO Pendant UA-002-08	collar (Fig. 1 indicates that the device was clipped near the collar & secured with a lanyard)	5 min	place: Taiwan (various locations) time: September 2013-February 2014 (total trial time), light measurement at baseline & end of study
Ostrin et al. (2018)	journal article	examination of objectively measured time outdoors, light exposure, activity & sleep in children during school & summer and assessment with eye growth as well as evaluation between parent and child behaviors	observation – longitudinal	Actiwatch Spectrum	wrist	1 min	place: Houston, Texas, USA time: January-May (spring school session), June-August (summer session), September-December (fall school session) (year: *not reported*)
Read, Vincent, et al. (2018)	journal article	comparison of daily light exposure patterns in similarly aged children from Australia and Singapore who are known to exhibit differences in myopia prevalence	reanalysis; methodological	Actiwatch 2; HOBO Pendant UA-002-08	Actiwatch: non-dominant wrist; HOBO: on shirt, fastened with safety pin, light sensor facing outward	Actiwatch: 30 s; HOBO: 5 min	Actiwatch: place: Brisbane, Australia time: September 2012-June 2013; HOBO: place: Singapore time: April-June 2011

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Landis et al. (2018)	journal article	evaluation of dim light exposure in myopia in children and adolescents	reanalysis	Actiwatch 2	non-dominant (cf. Read et al., 2014; 2015) wrist	30 s	place: Brisbane area, Queensland, Australia time: baseline ocular measurements May-November 2012 & 1st light measurement period over following 14 days, 2nd light measurement period 6 months later
Ulaganathan et al. (2019b)	journal article	investigation of the association between objectively measured ambient light exposure and longitudinal AL changes & their seasonal variations over 12 months in emmetropic & myopic young adults	observation – longitudinal	Actiwatch 2	non-dominant wrist	30 s	place: Brisbane, Australia time: May 2015-September 2015 (winter light measurement period), November 2015-February 2016 (summer light measurement period)
Wen et al. (2020)	journal article	reassessment of the association between near work, outdoor exposure & myopia in children with an objective approach	observation – cross-sectional	Clouclip	right arm of eyeglass frame (frames without lenses provided for subjects not wearing spectacles)	2 min	place: Ningxiang, Hunan Province, China time: *not reported*
Franklin (2020)	dissertation	exploration of average daily light exposure and impact of season, day of week & latitude on said exposure, assessment of time spent outdoors and provision of data on the influence of light exposure upon eye growth in UK school children	observation – longitudinal	Actiwatch 2	wrist	30 s	place: United Kingdom (various locations) time: May 2017-June 2019 (including baseline, year 1 & year 2 follow-up)
L. Li et al. (2020)	journal article	development of a practical approach to quantify the exposure to environmental risk factors of myopia	observation – cross-sectional; methodological	Clouclip	right side of spectacle frame (frames without lenses provided for subjects not wearing spectacles)	2 min	place: *not reported* – probably China (cf. affiliations) time: *not reported*

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

M. Li et al. (2021)	journal article	evaluation of the association of reported time outdoors and light exposure patterns with myopia in 9-year-old children from the Growing Up in Singapore Towards Healthy Outcomes (GUSTO) birth cohort	observation – cross-sectional	FitSight	wrist	1 min	place: Singapore time: *not reported*
Mirhajianmoghadam et al. (2021)	journal article	assessment of behaviors during COVID-19 in myopic and non-myopic children	observation – cross-sectional	Actiwatch Spectrum Plus	wrist	1 min	place: Houston area, Texas, USA time: July-August 2020
Bhandari et al. (2022)	journal article	subjective & objective assessment of behaviors in myopic and non-myopic school children in the US during the Covid-19 pandemic	observation – cross-sectional	Clouclip	mounted on right spectacle frame (glasses with plano spectacles provided for non-myopic children)	2 min	place: Houston, Texas time: December 2020-May 2021
X. He et al. (2022)	journal article	evaluation of dose-response efficiency of (increasing) time outdoors per school day over 2 years on myopia onset & shift	intervention; observation – longitudinal	Mumu	wrist	20 s	place: Shanghai, China time: October 2016-December 2018 (total trial time; light data collection during second year)
S.-M. Li et al. (2022)	journal article	investigation if SMS text messages to parents increase light exposure & time outdoors in school-aged children and provide effective myopia control	intervention; observation – longitudinal	HOBO Pendant UA-002-64	fixed on clothes, light sensor facing outward	10 s	place: Anyang, China time: May 2017-May 2018 (group allocation, then observation for 3 years; light data collection within 2 weeks before and after the intervention)

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

publication	device calibration & additional measurements[a]	visual measurements & respective classifications[b]	subjects[c]	measurement duration & protocol[a] (incl. compliance enhancement measures)
Backhouse et al. (2011)	*n/a*	cycloplegic autorefraction	N = 12 school-aged children; 13-14 years	7 days per measurement period; 3 measurement periods over 3 consecutive months
Dharani et al. (2012)	two persons wore device under five conditions: a) outdoors – bright sunny day, b) outdoors – dark cloudy day, c) indoors – enclosed space, d) indoors – near window with stream of bright sunlight, e) indoors – device not worn & left on table) → revealed overlap between b) and d)	subject groups: **myopic** (≤ -0.50D SER) & **non-myopic**, underlying measurements *not reported*	N = 117 children participating in Family Incentive (FIT) trial included in analysis; 6-12 years (M±SD 8.3±1.6); 57 female, 60 male; 103 Chinese, 8 Indian, 6 other subject groups: n = 65 myopic, n = 52 non-myopic exclusion criteria: medical conditions like type 1 diabetes, severe asthma, mental illness	continuously for 7 days; parental guidance; e-mails & phone calls once to ensure compliance

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Schmid et al. (2013)	measurements under different representative lighting conditions at place & time of year of study to categorize light data → see "IO-cut-off & other data categorization"	myopia (≤ -0.50D SER) & emmetropia (-0.25±1.00D SER) based on non-cycloplegic subjective refraction (maximum plus for best visual acuity methodology & blur back techniques) right eye measurements analyzed myopia progression status retrospectively determined from 2-3 years prior (initial measurement, IM) subject groups: **emmetropic** (both at IM & study time), **stable myopic** (myopia at IM & ≤0.25 D progression), **progressing myopic** (myopia at IM & ≥0.50 D progression)	N = 30 3rd- & 4th-year university students; 17-25 years; 77.1% female; 48.6% Asian, 49% European/white & 11.4% Indian; all best-corrected distance acuities at least 6/6 in each eye & no strabismus subject groups: n = 13 emmetropic (SER M±SD +0.11±0.39D), n = 12 stable myopic (SER M±SD -3.61±1.47D), n = 10 progressing myopic (SER M±SD -2.48±1.74D) exclusion criteria: hyperopia ≥ +1.50D, anisometropia ≥ 1.50D, astigmatism ≥ 1.50D, amblyopia, keratoconus, past myopia progression treatment	3 days (Wed, Fri, Sat); advised to wear during waking hours

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Alvarez and Wildsoet (2013)	sample light measurements with device at desk height & sensor pointing skyward in indoor environments frequented by subjects → never > 1,000 lux; simultaneous outdoor measurements with device, photometer (calibrated to CIE photopic function) & pyranometer for one day → discrepancies at high lux levels, explained with device sensitivity differences & coarser sampling interval for photometer & pyranometer; test of devices' responses mounted horizontally (sensor facing skyward) & vertically (sensor facing outward) for 1 h of simultaneous collection with 0.1 Hz sampling rate → vertical orientation on average (mean) 90% & 52% lower than horizontal outdoors in sunlight & indoors with non-directional light source, respectively	myopia (≤-1.00D SER) & emmetropia (0±0.50D SER) classified based on non-cycloplegic autorefraction (Grand Seiko WE-5100K) refractive errors reported as right eye SER	N = 27 UC Berkeley students; 18-25 years (M±SD 20.67±2); 17 females, 10 males; 48% Asian, 15% Caucasian, 37% other; all no anisometropia >1.50D, normal corrected visual acuity (20/20), age-appropriate accommodative amplitudes & facilities, no ocular health or binocular vision anomalies; 23 myopic (SER -1.06D - -8.56D, M±SD -3.76±2.09D; 39.1% progressing), 4 approx. emmetropic (SER M±SD -0.10±0.31) exclusion criteria (not conclusive): eye disease, refractive surgery	over 14 consecutive days, simultaneously for all subjects of the same season (n = 7 in spring, n = 10 in fall, n = 10 in winter); instructed to wear all day, every day & to place by bed when sleeping; daily morning text messages to encourage compliance

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Read et al. (2014)	all devices manufacturer-calibrated prior to study & pilot study in which they were mounted together on a board and carried through a range of lighting environments with a range of movements (recording every 30 s for 60 min) → inter-device intraclass correlation 0.99 for light data	subject groups: **myopes** (average SER from right & left eyes ≤ -0.50D, with at least one eye ≤ -0.75D) & **emmetropes** (average SER from right & left eyes < +1.25D and > -0.50D, with neither eye ≤ -0.75D) based upon non-cycloplegic spherical equivalent subjective refraction	N = 102 children enrolled in role of outdoor activity in myopia (ROAM) study; 10-15 years (M±SD 13.1±1.4); all normal best-corrected visual acuity of logMAR 0.00 or better, no history or evidence of significant ocular disease, no hyperopic refraction errors > +1.25D subject groups: n = 41 myopes (SER M±SD -2.39±1.50D, 51% female), n = 61 emmetropes (SER M±SD +0.34±0.30 D, 53% female), of which n = 41 were age & gender matched to a myope and wore device at the same time; similar distribution of age & gender among matched (n = 82; for both groups: mean age 13.0 years & 51.2% female) and unmatched (n = 20; mean age 13.4 years & 55.0% female) subjects *reported results based on the 82 matched myopes & emmetropes*	2 weeks (14 days) during school term; instructed to wear 24 h/day & to ensure no obstruction of device by clothing; if device was removed for any reason (e.g., swimming continuously for > 30 min or engaging in activity where watch-wearing was prohibited), asked to complete diary to document type of activity & environment (indoors/outdoors)

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Read et al. (2015)	see Read et al. (2014)	see Read et al. (2014) for subject groups; refractive error determination described here as non-cycloplegic subjective refraction aiming for maximum plus/least minus for best visual acuity & then binocular balancing for AL, five repeated measurements from both eyes taken with optical biometer (Lenstar LS 900) ocular measurements taken at baseline (prior 1st light measurement period) & every 6 months after that over 18 months, all scheduled between 3PM & 5PM to limit potential influence of diurnal AL changes upon data	N = 101 children (of 102, 1 excluded from analyses due to retinal dystrophy signs at 2nd visit) enrolled in ROAM study; 10-15 years; all best-corrected visual acuity of logMAR 0.00 or better in each eye, no history or evidence of significant ocular disease, no anisometropia > 1.25D subject groups (classified based on baseline measurement): n = 41 myopic (SER M±SD -2.39±1.50D; age M±SD 13.0±1.5 years; 51% female), n = 60 non-myopic (SER M±SD +0.34±0.30D; age M±SD 13.1±1.2 years; 52% female) exclusion criteria: non-cycloplegic hyperopic refractive errors of > +1.25D, any optical or pharmacological treatments to slow myopia progression over 18 months, 3 subjects lost to follow-up (2 after baseline, 1 after 2nd ocular measurement visit) & 4 excluded from analysis due to beginning orthokeratology contact lens wear (3 after 2nd, 1 after 3rd ocular measurement visit) → 99 subjects with data from at least 2 visits, 94 with complete data (59 non-myopic, 35 myopic subjects)	2x14 days during school academic term with 5.3-9.4 months (M±SD 6.4±0.7) between baseline & follow-up; measurement protocol similar to Read et al. (2014)

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Ostrin (2017)	5 randomly chosen devices mounted on holder with sensors oriented upwards & measured against calibrated luxmeter & UV sensor in 14 conditions (inside 10 buildings on University of Houston campus & in 4 outdoor locations) for 5 min & with 5 individual measurements with luxmeter & UV sensor → significant correlation (R^2 = 0.99) between ambient illuminance measured with devices & luxmeter for all conditions; no relationship between device & UV sensor measurements indoors, but correlation between increase in UV & higher ambient illuminance outdoors; 5 devices mounted on a holder with sensor directed upwards & measured light levels in various conditions (winter sun & shade, summer sun & shade, rooms in homes, elementary school classroom) for 7 days → rarely during summer sun, outdoors > 199,999 lux (devices' upper boundary, replaced by 200,000 lux), outdoor means during brightest 2 h/day averaged over days & devices 1,443 lux (winter shade) - 176,497 lux (summer sun), means in homes (7PM-9PM) 3.15 lux (home office) - 248 lux (family room), classroom during school hours mean 248 lux; 2 devices tested outdoors with 14% transmitting sunglasses placed over sensors at 10 mm & directed upwards in full sun & full cloud cover during summer (10 min each) → full sun mean 34,207 lux, full cloud cover mean 2,973 lux	subject groups: **emmetropic** & **myopic** subjects classified based on history & habitual correction	N = 55 adults; 21-64 years (M±SD 37.0±8.8); 24 males, 31 females subject groups: n = 18 emmetropic, n = 37 myopic	continuously for 14 days (n = 15 in winter, n = 19 in spring, n = 15 in summer, n = 6 in fall); instructed not to remove device (even during sleep) & to ensure that light sensor was unobstructed & not covered by clothes

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Wu et al. (2018)	light intensities measured with luxmeter at different areas of schools → ≥ 1,000 lux in any area outside classrooms	myopia (≤ -0.50D SER) classified based on cycloplegic autorefraction (KR-8100; 1 drop of 0.5% proparacaine followed by 1 drop of 1% tropicamide & 1% cyclopentolate hydrochloride administered 5 min apart; measurements 30 min after administration of initial drop & pupil size > 6 mm diameter; 5-8 consecutive readings) ocular assessments at baseline and end of study	N = 930 grade 1 school children enrolled in Recess Outside Classroom Trial 711 (or control group wait list); 6-7 years (M±SD 6.34±0.48); 47.85% female; 10.53% myopic (from n = 927, after exclusion of myopic children with current treatment) n = 693 completed full 1-year program (120 excluded for myopia treatment, 117 did not attend final assessments) – baseline characteristics (calculated from data given for trial & control group separately in Appendix): 65.08% 6 years, 34.92% 7 years; 52.38% male, 47.62% female; 8.95% myopic; SER M±SD 0.36±0.80D trial group, 0.41±0.82D control group exclusion criteria: best-corrected visual acuity not achieving 20/25, amblyopia, orthokeratology, atropine eye drop treatment *analysis based on the 693 children*	2x7 consecutive days; additional recording of activities in diary every half hour to determine outdoor activity time; teachers were responsible for reminding subjects to wear device at school & parents were informed about importance of using device & diary out of school

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Ostrin et al. (2018)	*n/a*	subject groups: **hyperopes** (> +2.00D SER), **emmetropes** (+2.00D - -0.25D SER) & **myopes** (< -0.25D SER) classified based on cycloplegic autorefraction (WAM-5500; eyes dilated with 0.5% proparacaine, 1% tropicamide, 2.5% phenylephrine; ≥ 5 measurements) of right eye for AL, 3 measurements averaged per eye (LenStar; after eye dilation) measurements taken at enrollment & after one year only right eye data included in analyses; SER similar between right and left eyes	N = 60 children (of 64, 4 lost to follow-up) from 38 families at one-year exam & analyzed; 5-10 years (recruited; M±SD 7.6±1.8); 24 females, 38 males; 45 Caucasian, 8 Asian, 4 Hispanic, 3 African American; all best-corrected visual acuity of 20/25 or better; baseline SER -2.41 - +7.75D (M±SD +0.85±1.49) subject groups (baseline): n = 5 hyperopes (SER M±SD +4.12±2.26D), n = 47 emmetropes (SER M±SD +0.86±0.50D), n = 8 myopes (SER M±SD -1.28±0.67D) exclusion criteria: ocular pathology, treatment for myopia (incl. atropine drugs or multifocal contact lenses)	3x continuously for 2 weeks across the year (2 school & 1 summer session per subject); instructed not to remove device for entire period

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Read, Vincent, et al. (2018)	pilot experiment in Brisbane to determine comparability between the two devices with 10 adults wearing them simultaneously (Actiwatch on non-dominant hand, HOBO fastened to shirt) for 60 min, light measures collected every 60 s, mean light exposure & minutes of outdoor light exposure analyzed within each subject → high correlation between both devices (*r* = 0.79 mean light exposure, *r* = 0.95 min of outdoor light exposure), M±SD 4,677±11,048 lux difference for mean light exposure (greater for HOBO; difference M±SD 104±151 lux for < 1,000 lux & M±SD 9,760±15,117 lux for > 1,000 lux), M±SD 0.4±1.1 min difference for outdoor light exposure times (more with HOBO) → mean light exposure levels overestimated with HOBO, but similar outdoor light exposure estimates & thus data analysis concentrated on measures of time exposed to > 1,000 lux for any measurements in the respective data acquisition studies, see Read et al. (2014) for Actiwatch & Dharani et al. (2012) for HOBO	subject groups: **myopic** (≤ -0.50D SER) & **non-myopic** (+1.25 - < -0.50D SER) see Read et al. (2014) for information on ocular measurement procedures for Actiwatch sample	N = 112 children with valid light exposure measures from ROAM study (n = 43; Actiwatch) or FIT trial, Singapore (n = 69; HOBO) analyzed; ROAM: 10-12 years (M±SD 11.3±0.6), FIT: 8-12 years (M±SD 9.2±1.1); ROAM: 44% female, FIT: 38% female; ROAM: 36 Caucasian, 6 East Asian, 1 South Asian, FIT: 64 East Asian, 5 South Asian; all residing in urban regions, good general health, best-corrected vision in both eyes logMAR 0.00 or better; all no history or evidence of ocular disease or hyperopic refraction error of > +1.25D; SER +1.16 - -9.06D (M±SD -1.57±2.05), ROAM: SER +1.00 – -6.25D (M±SD -0.71±1.43), FIT SER +1.16 - -9.06D (M±SD -2.14±2.22) subject groups: ROAM: n = 19 myopic & n = 24 non-myopic, FIT: n = 40 myopic & n = 29 non-myopic	Actiwatch: 2x14 days (separated by ca. 6 months) during school term, worn continuously for 24h/day; for more information on protocol see Read et al. (2014, 2015) HOBO: continuously over 7 days from waking until end of day, n = 40 children during school term & n = 29 children during school vacation; for more information on protocol see Dharani et al. (2012)

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Landis et al. (2018)	sensitivity of device at dim illuminance levels measured by comparison with calibrated luxmeter across 16 dim (0-40 lux) light levels by placing both devices in same room facing vertically upwards with device taking 3 readings per level, which were averaged → device's light sensor high agreement with luxmeter (R^2 = 0.9958; differences M±SD 2.1±1.1 lux with greater differences at higher levels), indicating high sensitivity for assessing dim lights	subject groups: **myopic** (average SER from right & left eyes ≤ -0.5D & at least one eye ≤ -0.75D) & **non-myopic** (average SER from right & left eyes < +1.25D and > -0.5D & neither eye ≤ -0.75D) based on non-cycloplegic subjective refraction aiming for maximum plus/least minus for best visual acuity ocular measurements at baseline, 6 months & 1 year later	N = 80 ROAM study participants analyzed; 10-15 years; all no history of ocular disease; all best-corrected VA of logMAR 0.00 or better in each eye subject groups (based on baseline measures): n = 40 myopic (SER M±SD -2.39±1.5D), n = 40 non-myopic (SER M±SD 0.34±0.3D); each myopic child paired with nonmyopic child of same sex & similar age, wearing device over same period, one additional pair excluded due to development of ocular pathology in non-myopic child	2x14 days 6 months apart; activity diary to record if watch removed (e.g., for sports practice or bathing); for more information on protocol see Read et al. (2014, 2015)

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Ulaganathan et al. (2019b)	*n/a*	subject groups: **emmetropes** (< 0.75D & > -0.75D SER) & **myopes** (≤ -0.75D SER) based on subjective, non-cycloplegic SER of right eye AL (i.e., distance from anterior corneal surface to retinal pigment epithelium) of right eye measured with Lenstar LS 900 between 9AM & 11AM to avoid diurnal AL variations influencing results prior each measurement session, subjects asked to view 5 m distance target binocularly with optimal distance spectacle correction for 10 min to minimize influence of previous activities on measurements AL measured every 6 months over 12 months: baseline May 2015-September 2015 (winter), follow-up 1 November 2015-February 2016 (summer), follow-up 2 May 2016-September 2016 (winter)	N = 43 Queensland University of Technology students completing baseline; 18-30 years (M±SD 21.9±3.8); 29 female, 14 male; all visual acuity of 0.00 logMAR or better & no anisometropia > 1.00D or cylindrical refraction > 1.25DC & no history or evidence of ocular or systemic diseases and/or ocular surgeries/injuries subject groups: n = 21 emmetropes (M±SD 21.9±3.7 years; SER +0.26 - -0.62D, M±SD +0.06±0.31), n = 22 myopes (M±SD 21.8±4.0 years; SER -0.75 - -8.25D, M±SD -3.76±2.11) → each myope paired with an emmetrope to wear device over same period & had AL measured during same week exclusion criteria: SER > +0.75D, conditions disruptive to habitual light exposure patterns (e.g. insomnia, night shift work), optical or pharmacological myopia control treatment (e.g. orthokeratology lenses, multifocal spectacle/contact lenses, atropine), rigid contact lenses; regular spherical soft contact lens wearers included (n = 2) & asked to not use on measurement days all enrolled subjects wore device in winter & n = 37 (19 myopes, 18 emmetropes) in summer	2x14 days (1x winter, 1x summer), worn continuously for 24h/day; instructed to ensure that sensor was not covered by clothing; for details on protocol, referred to Ulaganathan et al. (2017), where the following is reported: advised to remove device only if planning to be in water for > 30 min & if device was removed, they recorded type, duration & environment (indoors/outdoors) of the activity performed during removal in diary

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Wen et al. (2020)	*n/a*	subject groups: **myopic** (≤ -0.5D SER) & **non-myopic** based on cycloplegic autorefraction (AR-1; 3 cycles of cyclopentolate 1% (1 drop) instilled 5 min apart, cycloplegic status tested with light reflex 30 min later)	N = 86 5th graders from Lao Liangcang Primary School in Ningxiang; M±SD 10.31±0.48 years; 42 (48.84%) male, 44 (51.16%) female; SER M±SD -0.35±1.26D subject groups: n = 28 (32.56%) myopic, n = 58 (67.44%) non-myopic inclusion criteria: normal ocular health, SER -6.00D - +1.00D, anisometropia of < 1.00D	continuously for 1 week (5 weekdays, 2 weekend days); required to wear during day, except for bathing & sleeping; teachers & parents asked to check whether subjects wore device to improve compliance
Franklin (2020)	all devices carried through 4 environments (indoors/outdoors, high/low illuminance) side-by-side for 15 min each with 15 s logging interval → all except 2 devices (one broken) ≥ 0.99 correlation coefficient, same in repeat study; after manufacturer repaired/replaced the 2 devices, 1.00 correlation coefficient with 2 others; investigation of degree to which device's rotational orientation may affect light exposure readings by placing 5 devices in touching proximity at 5 orientations & recording light intensity in the 4 conditions as above (15 min each, logging every 30 s) → significant difference in illuminance in all orientations across all conditions and all tested orientations (0, 45, 90 degrees)	myopia (≤ -0.50D SER in at least one eye) & emmetropia (> -0.50D & < +2.00D SER in both eyes), hyperopia (≥ 2.00D SER in at least one eye & neither eye myopic) based on objective cycloplegic autorefraction (WAM-550; while focusing on 3 m distance target; 1 drop of 1.0% cyclopentolate hydrochloride & < 2D defined as acceptable level of residual accommodation – if not after 40 min in subjects with darker irises, additional drop; 10 measurements taken per eye & averaged) AL measured with ocular biometer (Aladdin), after cycloplegia visual measurements taken at baseline, 1-year & 2-year follow-up (each 12 months ± 6 weeks apart)	N = 68 school children analyzed; 7.5-11.3 years (M±SD 9.2±1.1); 61.8% female; 85.9% white, 4.7% Asian, 1.6% Chinese, 7.8% mixed (information available for 95.6% of subjects); -4.75D - +5.57D SER (M±SD +1.20±1.44D); 3 (4.4%) myopic, 11 (16.2%) hyperopic, 54 (79.4%) emmetropic exclusion criteria: previous adverse reaction to or medicine that may interact with cycloplegic drops, ocular condition requiring medication, past/present myopia control intervention (atropine, orthokeratology, multifocal soft contact lenses, bifocal or progressive addition spectacle lenses) *reported results based on subsample of n = 25 subjects with valid summer data & longitudinal eye growth data and for which no separate information on demographics is available*	11 days during school term (recording Fri 12PM-Mon 12PM) with 12 months ± 6 weeks between baseline, year 1 & year 2 follow-up; advised to wear 24 h/day & prevent clothing obstruction; originally advised that waterproof for 1 m for ≤ 30 min, but later found that seals were prone to leaking in 40°C, thus advised not to swim, shower, or bath with device *in results reported here, only light exposure data of summer seasons (i.e., collected during British Summer Time) included*

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

L. Li et al. (2020)	*n/a*	myopia (SER ≤ -0.5D) based on cycloplegic autorefraction average SER from both eyes used for analyses	N = 179 fourth graders recruited from 3 schools; M±SD 9.17±0.52 years; 92 male; M±SD 0.22±1.18D SER; 33 (18.44%) myopic inclusion criteria: normal ocular health (except refractive error), anisometropia of < 1.00D	continuously for 1 week (5 weekdays & 2 weekend days); required to wear throughout day, except when bathing & sleeping; teachers & parents asked to check whether subjects wore device to improve compliance
M. Li et al. (2021)	*n/a*	subject groups: **myopia** (≤ -0.5D SER) & **non-myopia** based on cycloplegic (3 drops of 1% cyclopentolate hydrochloride, instilled 5 min apart) autorefraction (Canon RK5/RK-F2, performed ≥ 30 min after 1st drop, with pupil dilation ≥ 6 mm) AL assessed with optical biometer (IOL Master 500) paired eyes analyzed	N = 483 children (of 716 returning to 9-year-visit of GUSTO birth cohort) analyzed; 9 years; 50.0% male; 59.8% Chinese; M±SD -0.61±1.83D SER; subject groups: n = 204 (42.2%) myopes, n = 279 (57.8%) non-myopes (applied) exclusion criteria: myopia treatment (orthokeratology, atropine)	14 days, recording during daylight hours (7 AM-7 PM)
Mirhajianmoghadam et al. (2021)	*n/a*	subject groups: **myopes** & **non-myopes** based on questionnaire using indirect method technique (i.e., series of questions about use of eyeglasses & age of first dispensing)	N = 53 children; 5-12 years (M±SD 8.3± 2.4); 39 white, 7 African American, 5 Asian, 1 mixed, 1 unknown (parent report); 43 non-Hispanic, 10 Hispanic (self-report) subject groups: n = 14 myopes (M±SD 8.9±2.3 years), n = 39 non-myopes (M±SD 8.1±2.4 years)	continuously for 10 days & nights during Covid-19 related quarantine measures

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Bhandari et al. (2022)	devices validated for illuminance as described in Bhandari and Ostrin (2020), where the following is reported: devices mounted to spectacle frame & placed in various indoor & outdoor locations in shade & full illumination, light levels compared with luxmeter (sensor oriented along line of sight at same level as device), each light level for ≥ 4 min & ≥ 2 measurements, 2 min apart, recorded with luxmeter → results *not reported* in Bhandari et al. (2022)	subject groups: **myopes** & **non-myopes** based on University of Houston Near Work, Environment, Activity, and Refraction (UH NEAR) questionnaire with a series of questions about use of eyeglasses & age of first dispensing & further confirmation by observing refractive correction worn when dispensing study material	N = 40 (of 58 enrolled) children analyzed; 10-18 years (M±SD 14.6±0.4); 22 Asian, 14 White, 2 African-American, 1 American Indian or Alaskan native, 1 other (parent report); 37 non-Hispanic, 3 Hispanic subject groups: n = 25 myopes, n = 15 non-myopes; age distribution similar between groups, Asian children more likely myopic than non-Asian children	1 week during virtual online schooling for most participants (only n = 2 non-myopic children reported attending in-person classes)
X. He et al. (2022)	*n/a*	myopia (right eye ≤ -0.50D SER), hyperopia (≥ +2.00D SER), emmetropia (SER ≥ -0.50D & ≤ + 0.75D) based on cycloplegic autorefraction (KR-8900; 2 (3 if insufficient) drops of 1% cyclopentolate 5 min apart & refractive error assessed 40 min later when pupils > 6 mm with no light reflex); incident myopia: myopia development in children non-myopic at baseline AL measured with optical biometer (IOL Master; measured 3x/eye, if difference between any 2 measurements > 0.05 mm, repeated until difference below that) only right eye data analyzed & only children with full myopia included in analysis of myopia onset & myopic shift	N = 6,295 grade I & grade II school children enrolled in Shanghai Time Outside to Reduce Myopia (STORM) trial; 6-9 years (M±SD 7.2±0.7); 3,346 (53.2%) male, 2,949 (46.8%) female; M±SD +1.00±1.01D SER; 429 (6.8%) myopes, 5866 (91.2%) non-myopes exclusion criteria: strabismus, amblyopia, myopia control treatment strategies (e.g., atropine, orthokeratology lens), refusing cycloplegia 5,067 & 5,340 subjects eligible for 2-year cumulative incidence & progression analysis, respectively	required to wear device every day from 7 AM to 8 PM throughout second trial year

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

S.-M. Li et al. (2022)	*n/a*	myopia (SER < -0.5D) based on cycloplegic autorefraction (HRK-7000A; 2 drops of 1% cyclopentolate 5 min apart; refractive error assessed 30 min after last drop; 3 measurements averaged) AL measured with ocular biometry system (Lenstar LS900; 5 measurements averaged) only right eye data analyzed	N = 268 grade 2 students at baseline (n = 135 SMS group, n = 133 control group); M±SD 8.4±0.3 years; 147 (54.9%) male, 121 (45.1%) female; SMS: M±SD 0.66±1.05D SER, control: M±SD 0.37±1.34D SER; SMS: 19 (14.3%) myopic, 114 (85.7%) non-myopic, control: 23 (17.3%) myopic, 110 (82.7%) non-myopic inclusion criteria: best-corrected visual acuity of 20/20 or better in both eyes; -6.0D ≤ SER ≤ 1.5D & astigmatism < 1.5D per eye & anisometropia > 1.0D; no strabismus, amblyopia, or other ocular or systemic disease that may affect myopia development; ability to cooperate with ocular examinations & survey; no other myopia control intervention than school-based eye exercises *of these participants, 261 took part in complete study & were analyzed*	3 randomly selected days (2 weekdays, 1 weekend day) within 2 weeks prior & 2 weeks after intervention, respectively, recording time from 7 AM to 7 AM the following day; free annual ocular examinations & counseling for all children to help achieve good compliance

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

publication	data pre-processing (in-/exclusion, replacement procedures & rates)[a]	IO-cut-off & other data categorization[a]	main results & conclusion on light-myopia associations	comments
Backhouse et al. (2011)	*n/a*	IO-cut-off: > 1,000 lux to calculate amount of time spent outdoors amount of time spent indoors calculated from time in 10-1,000 lux	no significant correlation between refractive error & cumulative light exposure or between change in refractive error & cumulative light experienced over the 3 months measurement period	albeit longitudinal, the study only covered 3 months, and the change in refractive error was calculated from measurements directly before & after the 3 months of light data acquisition
Dharani et al. (2012)	for any day with all light measurements < 100 lux, assumption that child forgot wearing device & exclusion of day from analysis → exclusion rate *not reported* time outdoors derived from data from 7 AM to 7 PM	IO-cut-off: > 1,000 lux to assess outdoor time, based on similar IO-cut-offs from previous studies (Alvarez & Wildsoet, 2011; Backhouse et al., 2010, July 27)	time outdoors (h/day) not significantly different between myopic and non-myopic subjects for both weekdays and weekend days	
Schmid et al. (2013)	*n/a*	IO-cut-off: > 10,000 lux (most definitely outdoors) & > 500 lux (some bright indoor activity potentially included) categories chosen based on measurements described in "device calibration & additional measurements": sunlight (≥ 30,000 lux), outdoor shade (10,000-30,000 lux), bright indoor/dim outdoor light (500-10,000 lux), dim room illumination (< 500 lux)	no significant difference in daily illuminance, amount of time per day in each light data category/condition or number of daily alternations from indoors to outdoors (respective IO-cut-off: *not reported*) between subject groups; no correlation between daily illuminance & refractive error	

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Alvarez and Wildsoet (2013)	only data between sunrise & sunset analyzed	IO-cut-off: ≥ 1,000 lux measurements as "outdoor exposure", citing other literature (Backhouse et al., 2010, July 27; Dharani et al., 2012) & referring to sample light measurements indoors (cf. "additional measurements") never exceeding 1,000 lux; Initially, an 882 lux IO-cut-off was used based on local solar radiation data, outdoor measurements on typical day during study & indoor measurements, but there were no significant differences in the data analysis outcomes between the 882 lux & 1,000 lux IO-cut-offs, so 1,000 lux was used for the sake of consistency with the aforementioned literature bright sunlight: > 10^5 lux	no correlations between refractive error (D) and the analyzed light exposure measurements (mean maximum daily light intensity, average daily light intensity, mean % of daily time spent outdoors, mean daily time spent in bright sunlight, mean daily transitions between indoors & outdoors, solar-normalized cumulative light exposure)	some information on additional measurements, subjects & main results taken from Alvarez (2012)

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Read et al. (2014)	removal of invalid data (i.e., ≥ 15 min complete inactivity (indicates device removal) and/or complete darkness during daytime (indicates covered light sensor) → accounted for M±SD 6±11% of total data; for any of "off wrist" times documented in diary by subject, light level estimated based upon average of light levels measured 5 min prior & 5 min after device removal if these light levels were consistent with diary as indoors (<1,000 lux) or outdoors (>1,000 lux) – in case of inconsistency, which only occurred for diary-recorded outdoor activities, the mean outdoor light level over the same period of time, averaged across all other measured days, used as estimate & only days including ≥ 90% valid data included in analysis to determine average min/day in > 1,000 lux → exclusion of one subject with only 7 h valid data overall; for remaining 101 subjects, M±SD 13.4±1.5 valid days (range: 6.0-14.0) & final data analyzed included M±SD 32±50 min (range: 0-271) of data per day estimated with diary (ca. 2% of data used) 6 AM-6 PM considered for calculation of daily light exposure, but e.g. daily pattern of light exposure analyzed throughout 24 h	IO-cut-off: > 1,000 lux to estimate daily minutes in outdoor light levels, citing other literature (Dharani et al., 2012; Goulet et al., 2007; Guillemette et al., 1998) daily minutes in > 1,000 lux, > 2,000 lux & > 3,000 lux examined in ROC curve analyses	emmetropes significantly greater daily light exposure than myopes; emmetropes significantly greater light exposure between 10 AM & 12 noon, 1 PM & 2 PM & 2 PM & 3 PM than myopes & no group differences at other times (all days considered), only significant for 1 PM-2 PM in both weekends and weekdays (if considered separately); emmetropes significantly more time in > 1,000 lux than myopes (difference 36 min/day) with a nonsignificant tendency of a greater difference on weekends than weekdays; in multivariate analysis, only daily time exposed to > 1,000 lux – and not e.g. daily time of moderate to vigorous activity or near work – independently, significantly associated with refractive error; in ROC analyses, all light exposure metrics (mean daily light exposure, minutes in > 1,000, > 2,000 and > 5,000 lux) significantly discriminated myopic from emmetropic subjects, with time in 2,000 lux showing best performance

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Read et al. (2015)	see Read et al. (2014) → over both measurement periods, M±SD 26.2±3.1 days of valid light exposure data (M±SD 13.4±1.5 days from 1st measurement period, M±SD 13.1±1.7 days from 2nd measurement period); between-session reliability of average daily light exposure measurements: 0.759 mean daily light exposure between 6 AM & 6 PM used as primary light exposure measure; mean light exposure during other times uniformly low (6 PM-6 AM light exposure M±SD 7±5 lux & on average < 30 s/day exposure to > 1,000 lux)	IO-cut-off: *not relevant* intensity thresholds of > 1,000 lux, > 2,000 lux, > 3,000 lux & > 5,000 lux to examine potential associations of eye growth with light exposure above certain intensity	mean daily light exposure over both measurement periods significantly lower in myopic than non-myopic subjects, not dependent on season (i.e., warmer or cooler measurement period); greater light exposure significantly associated with smaller longitudinal AL changes; significant associations between greater light exposure & less axial growth for mean (log) daily minutes of exposure to > 3,000 lux & > 5,000 lux and no significant association for > 1,000 lux & > 2,000 lux; AL changes over time varied significantly between groups receiving low, moderate or high light exposure based on tertile split, with children with low light exposure exhibiting significantly greater axial eye growth than those with high and moderate light exposure & no significant difference between high and moderate light exposure groups; significant association between axial growth and both light exposure group & refractive error group (greater in myopic group) without interaction between them, suggesting independent effects	1st measurement period equals Read et al.'s (2014) data acquisition period

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Ostrin (2017)	light exposure data only included if device was worn the entire day; days excluded if subject removed device for > 30 min, or if light exposure dropped to 0 for ≥ 30 min during daylight (indicating obstruction); nights excluded if subject removed device for all or part of night → days included M±SD 13.2±1.4 → nights included M±SD 14.2±1.3	IO-cut-off: ≥ 1,000 lux classified as outdoor light; in Discussion, no indoor values having been recorded > 1,000 lux given as reason for assuming measures > 1,000 lux as being outdoors light grading: darkness (< 9 lux), dim indoor light (10-99 lux), standard indoor light (100-999 lux), standard outdoor light (1,000-9,999 lux), bright outdoor light (> 10,000 lux) light parameters described as adapted from previous validation studies using a similar wrist-worn Actiwatch accelerometer in adults (Alvarez & Wildsoet, 2013) and as having been used in a publication with children (Read et al., 2014)[d]	no significant difference in objectively measured time outdoors between emmetropic and myopic subjects; no significant difference in daily white light exposure between emmetropic and myopic subjects

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Wu et al. (2018)	out of school, device wearing compliance decreased, so device only used to calculate outdoor time during school time (weekday mornings & Tuesday afternoons) & diary log used when not in school; 96% compliance of wearing device at the end of study during weekday in-school time *the results reported here are based on in-school measurements only*	IO-cut-off: ≥ 1,000 lux to calculate time outdoors, based on "additional measurements" additionally, total minutes of exposure to ≥ 3,000 lux, ≥ 5,000 lux & ≥ 10,000 lux calculated	after separation of all subjects into groups based on weekly in-school outdoor time (< 125 min, 125-199 min, ≥ 200 min) in various intensities (≥ 1,000 lux, ≥ 3,000 lux, ≥ 5,000 lux & ≥ 10,000 lux), those with ≥ 200 min in ≥ 1,000 lux & ≥ 3,000 lux exhibited significantly less myopic shift than the respective < 125 min group both for all subjects & for those without myopia at baseline only (for ≥ 5,000 lux, said association only found in those without myopia at baseline & for ≥ 10,000 lux, too few observations for ≥ 200 min to test this cut-off in this group); for 125-199 min vs. < 125 min, this was only true for subjects without myopia at baseline & the ≥ 10,000 lux cut-off – suggesting that for school children with less outdoor time, high bright light intensities may be necessary to achieve protective effects, while moderate intensities may be enough for those with longer durations	results (& many methods) of the intervention trial are not reported here, as only the reported results of a post-hoc analysis on different durations of weekly outdoor time measured with the device during school hours and SER changes are within the review's scope

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Ostrin et al. (2018)	data only included if device worn for entire day, thus partial first & last days excluded; data excluded if device removed for ≥ 30 min or if light exposure dropped to 0 for ≥ 30 min during daylight hours (indicating sensor obstruction) → M±SD 13.9±2.9 days included in analysis per subject per session → ca. 18 days (< 1%) of data removed due to obstructed light sensor for all subjects over all 3 seasons	IO-cut-off: minutes exposed to > 1,000 lux as approximation for time spent outdoors during daylight hours, citing other literature (Dharani et al., 2012; Ostrin, 2017) additionally, mean exposure time to > 2,000 lux, > 5,000 lux, > 10,000 lux & > 50,000 lux calculated light parameters described as adapted from previous validation studies with similar wrist-worn Actiwatch accelerometer in children (Deng et al., 2010; Guo et al., 2013)[d]	mean daily white light exposure & time exposed to outdoor light not significantly correlated with AL growth, but negative directionality; controlling for baseline AL, age, sex, activity & parental myopic status: small, but non-significant effect of average daily white light exposure on AL at 1 year, but after exclusion of an influential observation, directionality was not given anymore & analysis did not reach significance, and similar findings occurred in repeated analysis using estimated amounts of light exposure adjusted for amount of available sunlight; controlling for baseline SER, age, sex, activity & parental myopia status: small, non-significant effect of average daily white light exposure on SER at 1 year detected, which was also non-significant after exclusion of the same influential observation; for no ambient illumination threshold (> 1,000 lux, > 2,000 lux, > 5,000 lux, > 10,000 lux, > 50,000 lux), significant effects of refractive group (myopes vs. emmetropes only) or significant differences in seasonal effects between refractive groups	red and blue light exposure were also analyzed, but not included here due to the focus on illuminance measurements

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Read, Vincent, et al. (2018)	Actiwatch: M±SD 25.4±3.3 days (out of 28) of valid light exposure available for analysis; data resampled at 5 min intervals for comparability with HOBO data HOBO: M±SD 6.6±0.7 days (out of 7) of valid light exposure available for analysis; only weekend data included for children who wore device during school vacation & analyses comparing daily minutes of exposure to > 1,000 lux on weekends between data collected during school term & school vacation revealed no significant difference for both data sets, data recorded between 7 AM & 7 PM each day analyzed	IO-cut-off: minutes in > 1,000 lux as minutes of outdoor light exposure, citing the publications whose results are reanalyzed (Dharani et al., 2012; Read et al., 2014, 2015)	no significant effect of refractive group upon mean hourly outdoor light exposure overall, but myopic children in Australia received significantly lower outdoor light exposure than non-myopic children in Australia, while no such effect was observed in Singapore; no significant effect of refractive group upon outdoor light exposure either within or outside of school hours, respectively; no significant effect of refractive group on number of outdoor episodes (i.e., instances of continuous exposure to > 1,000 lux for ≥ 5 min)	reanalysis & comparison of data reported in Read et al. (2014, 2015) & Dharani et al. (2012)

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Landis et al. (2018)	activity diary used to estimate illuminance during times when the device was not worn day eliminated from analyses if device removed for > 90% of day (documented in diary) → M±SD of 23.5±0.34 days per subject included (over both measurement periods) only data during waking hours used as determined by Actiwatch sleep & wake detection algorithms and diaries → myopic & non-myopic children equal amounts of time awake/day data from both measurement periods combined as they did not differ significantly in light exposure or time awake	IO-cut-off: > 1,000 lux classified as outdoor light exposure four light intensity categories: scotopic (< 1-1 lux), mesopic (1-30 lux), indoor photopic (> 30-1,000 lux) & outdoor photopic (> 1,000 lux) light; based on similar studies in case of higher light intensity and on device's ability to detect dim light in case of scotopic light threshold, see "additional measurements"	daily light exposure patterns across light levels & weekend (WE)/weekdays (WD) that were found to differ significantly between myopic and non-myopic participants, or only found in one group: amount of exposure to the individual light levels: myopic children less scotopic light during WE than non-myopic, scotopic light exposure in non-myopic children higher on WE than WD, non-myopic children more time in mesopic light on WE than WD, myopic children more time in mesopic light than non-myopic on WE & myopic children more indoor photopic light than non-myopic on WE, non-myopic children more outdoor photopic light than myopic on WE; average time (h/day) in light levels on WE/WD: non-myopic children more time in scotopic light during WE than WD, myopic children more time in mesopic light than non-myopic on WD and WE, myopic children less time in outdoor photopic light than non-myopic on WE & similar non-significant trend on WD; comparison of average of initial & 1-year follow-up refractive status with time in each intensity: no association for non-myopic, but lower daily outdoor photopic & higher mesopic light exposure significantly correlated with more myopic refractive errors in myopic children (no significant association for other levels – but scotopic light similar pattern as outdoor photopic)	reanalysis of data from Read et al. (2014, 2015)

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Ulaganathan et al. (2019b)	for data screening, referred to Ulaganathan et al. (2017), where the following is described: removal of any invalid data where there was evidence of device removal for ≥ 15 min (i.e., complete inactivity and/or complete darkness during day) & light levels at these times estimated based upon average level 5 min before removal if these levels consistent with diary report of activity during removal – if not, deletion of off-wrist period data → 2 (4) emmetropes (myopes) < 5 valid data days in summer & thus excluded as < 7 days provide significantly lower personal light exposure reliability estimates in young adults (Ulaganathan et al., 2017) → light data from 21 (16) emmetropes & 22 (15) myopes analyzed for winter (summer) → on average, each subject 13.5±2.0 (13.3±1.8) days of valid light measures in winter (summer) night-time defined as 6 PM-6 AM	IO-cut-off: daily time of exposure to > 1,000 lux to estimate daily outdoor time	daily time in > 1,000 lux not significantly different between emmetropes & myopes averaged over both seasons, but significantly longer daily > 1,000 lux exposure in summer than winter for both groups with significantly higher seasonal difference in emmetropes than myopes; daily > 1,000 lux exposure significantly longer in emmetropes than myopes in summer & no significant difference in winter; mean night-time light exposure slightly, significantly higher in emmetropes than myopes due to emmetropes exposed to higher light levels between 7 PM & 9 PM; greater daily > 1,000 lux exposure associated with smaller longitudinal AL changes with a negative association between AL changes & daily > 1,000 lux exposure in summer & winter, but only significant in winter; no significant association between night-time light exposure & longitudinal AL changes; emmetropes (other than myopes) small AL reduction in summer, which together with their exposure to significantly higher light levels in summer suggests inverse relationship between seasonal AL differences & light levels; significant moderate negative association between seasonal difference in AL change & in daily time exposed to bright lights, i.e. subjects with greater daily light exposure in summer than winter exhibited less AL change in summer than winter & vice versa

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Wen et al. (2020)	only data obtained from at least 80% of total required wearing time during day considered valid; subject's data set valid if it spanned at least 3 days during week & 1 day during weekend → mean daily device wearing time: M±SD 11.72±1.14 h → mean valid weekdays (weekend days): M±SD 3.98±0.36 (1.13±0.11) data between 7 AM & 8 PM used for analysis as vast majority of light exposure & near work occurred within this period for all subjects	IO-cut-off: ≥ 1,000 lux as outdoor exposure additional light intensity thresholds to calculate average daily exposure time: > 2,000 lux, > 3,000 lux, > 5,000 lux	myopic & non-myopic children similar temporal light exposure patterns, but some variations: significantly greater light intensity experienced by non-myopic than myopic children 10:10 AM-10:30 AM, 12:20 PM-14:10 PM & 16:00 PM-17:30 PM; no significant difference between refractive groups in average daily exposure duration to > 1,000 lux & > 2,000 lux, but myopic children exposed to > 3,000 lux & > 5,000 lux for significantly shorter durations than non-myopic; no significant difference between refractive groups for average daily light intensity & average frequency of continuous outdoor exposure (i.e., number of transitions between indoor & outdoor exposure); time spent in > 3,000 lux & time spent in > 5,000 lux found to be protective against myopia in two independent analyses

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Franklin (2020)	167 data acquisition sessions from 109 participants → 18 unsuccessful & removed → 149 successful data sets screened for compliance only full days included → 9-day period; removal of invalid data (i.e., ≥ 15 min with 0 activity (indicates watch removal) and/or 0.01 lux recorded during daytime (7 AM-7 PM; indicates covered light sensor)) & only days including 90% of valid data during daytime included – for these days, substitution of removed data with average data for same time period on valid days → 39.7% of collected days invalid & removed; analysis only performed on data sets with at least 5 valid days → 36.2% of data sets removed → 95 data sets from 68 subjects included → 1.1% of analyzed light exposure data based upon substitution daily light exposure derived from measurements from 7 AM-7 PM	IO-cut-off: > 1,000 lux to estimate outdoor exposure due to establishment of cut-off in studies on light levels and change in refractive error (Alvarez & Wildsoet, 2013; Dharani et al., 2012; Ostrin, 2017; Ostrin et al., 2018; Read et al., 2014, 2015)	no significant correlation between AL growth and daily light exposure or daily outdoor time; no significant difference in AL between groups receiving low, average or high exposure based on tertile split of average daily light exposure & also not between groups experiencing low, average, or high outdoor exposure	the stated purpose of the study refers to the respective chapter (9) rather than the entire dissertation

Supplementary Table C3 – Continued
Detailed Information About the Included Publications

L. Li et al. (2020)	data preprocessing in creation of working distance (WD) – light intensity (LI) space: 1) denoising raw data with fast Fourier transformation & inverse fast Fourier transformation after scaling LI with log_{10} → smoother data with more explicit distributions, 2) creating 2-dimensional space for WD & LI where both variables were continuously measured as a time series, summarized in 40x40 pixels heatmap, each pixel representing specific circumstance (specific WD & LI) in which visual behavior occurred & pixel color representing percentage of time (PoT) spent in this circumstance → PoT in each pixel = ratio of time falling into pixel to total measured time for each subject; 3) dealing with sparsity in WD-LI measurements: "borrowing" information from neighboring pixels behavior for each pixel to address sparsity by using 2-dimensional Gaussian kernel function	*not relevant*	shorter WD & lower LI generally manifested detrimental effect on refractive error towards myopia; strength of impact of both factors varied with relative level between them: split up, limit of statistical significance (i.e., detrimental effect related to myopia) ca. 40 cm for WD & ca. 6300 lux for LI – so for WD of > 40 cm, near work no detrimental effect toward myopia regardless of LI & for eye-level LI > 6,300 lux, LI^e no detrimental effect on refractive error toward myopia regardless of WD, but for < 40 cm WD or < 6,300 lux eye-level LI, final impact of one factor depends on other; under < 10 lux LI, < 20 cm WD modest protective effect against myopia; proposed parameter "visual behavior index (VBI), calculated from subject's PoT of each pixel & influence of each pixel on SER to theoretically reflect overall effect, significantly positively related to SER – when VBI increased (decreased), SER towards hyperopia (myopia)	in this study, it was aimed at establishing a parameter (VBI) to quantify exposure to environmental risk factors (WD & LI) by mapping them in a two-dimensional space – therefore, not all of this table's categories apply well, but since results on the association between light exposure & myopia are reported, the publication is included here and some results on WD are also presented as they are closely related to those on LI due to the VBI

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

M. Li et al. (2021)	light data excluded for poor compliance, if (1) missing at least 1 weekday & 1 weekend of device wear, (2) wear days with average daily light intensity of ≤ 100 lux or proportion of 0 lux entries ≥ 60% per day (considered implausibly low & highly suggested covered sensor over extended period) → 93 (16.1%) subjects excluded (n = 72 for (1), n = 21 for (2)) → thus, 483 of 576 subjects with light data included device recorded light levels during daylight hours 7 AM-7 PM	IO-cut-off: ≥ 1,000 lux for outdoor environments, citing prior literature (Ostrin et al., 2018; Read et al., 2014; Verkicharla et al., 2017; Wu et al., 2018) additional increasing light level cut-offs analyzed: ≥ 3,000 lux, ≥ 5,000 lux, ≥ 15,000 lux	average light levels (outdoor only & overall) & duration of daily light exposure (≥ 1,000 lux) not associated with myopia, SER or AL in multivariable analyses adjusted for covariates (gender, ethnicity, near-work, number myopic parents, maternal education & for AL models, also height); no associations between duration of light exposure at higher cut-offs (≥ 3,000 lux, ≥ 5,000 lux, ≥ 15,000 lux), timing of light levels or duration of light exposure at different periods during daylight hours or number & duration of daily light exposure episodes (≥ 1,000 lux continuously for ≥ 5 min) with myopia, SER or AL; average outdoor light levels significantly associated with myopia, but not SER or AL, in univariable analysis (no significant association with any outcome for light level overall or daily duration of light exposure in univariable analyses); when stratified by weekdays & weekend, average outdoor light levels on weekdays associated with lower odds of myopia, but not with SER or AL; longer duration of light exposure episodes on weekdays associated with shorter AL; light levels or duration of light exposure episodes on weekend not associated with myopia, SER or AL; duration, timing or frequency of light exposure on either weekday or weekend not associated with myopia, SER or AL

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

Mirhajianmoghadam et al. (2021)	→ device worn for M±SD 7±1 weekdays & M±SD 2.4±0.7 weekend days	IO-cut-off: > 1,000 lux as outdoors, citing other literature (Dharani et al., 2012; Ostrin et al., 2018; Read et al., 2014)	During COVID-19 & compared to non-myopic children, myopic children significantly lower daily light exposure & tended to spend non-significantly less time outdoors	
Bhandari et al. (2022)	only days with ≥ 8h of Clouclip data during wake time considered valid; ≥ 3 valid weekdays & ≥ 1 valid weekend day required for subject to be included in analysis → for n = 18 subjects, data not valid (some not compliant with wearing, some ≤ 8 h/day of valid data) → mean valid days (of included subjects) 6.6±0.7 (range 4-6) → average daily wear time 15.1±0.2h (13.7±1.6h) for weekdays (weekend days), mean 14.7±0.2h, similar between refractive error groups data collected from wake to bed time	IO-cut-off: duration exposed to illuminance ≥ 1,000 lux as time outdoors, citing other literature (Dharani et al., 2012; Ostrin, 2017; Read et al., 2014) additionally, duration in the following light intensities analyzed: < 1,000 lux (indoors), > 2,000 lux, > 3,000 lux & > 5,000 lux (all outdoors)	daily white light exposure & time outdoors significantly less for myopes than non-myopes; no refractive error group difference in average daily number of transitions from indoor to outdoor; myopes significantly more time indoors & significantly less time in all thresholds of outdoor light levels than non-myopes; when analyzed by period of the day (school, after school, nighttime), significantly lower white light exposure & time outdoors for myopes than non-myopes during school period	children also wore Actiwatch Spectrum Plus, but not for illuminance analysis, so information regarding the Actiwatch (e.g. calibration measures, wearing protocol) is not included here

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

X. He et al. (2022)	required to wear device daily from 7 AM-7 PM	IO-cut-off: data classification as "indoor" & "outdoor" based on machine-learning-based support-vector machine (SVM) model (Ye et al., 2019), and the variables lux, UV, and steps as measured by the device are reported to have been used in model building (Ye et al., 2019); *see comment column for further explanation*	post-hoc analysis over all subjects: no variation in 2nd year myopia incidence by indoor light intensity, but reduction in myopia incidence observed with increasing level of outdoor light intensity & increasing outdoor time; analysis of individual time & light variables: increasing time outdoors significantly reduced risk of incident myopia & cumulative outdoor lux/day significantly reduced risk of myopia onset, but myopia incidence not associated with time indoors or indoor light intensity; reduced shift in SER & AL with increasing outdoor time; increasing cumulative outdoor lux/day associated with reduced myopic shift in SER & AL; protective effects of outdoor time on myopic shift in SER & AL observed only in non-myopes, not in those already myopic; those already myopic significantly less outdoor exposure than non-myopes; pooled data of all subjects indicated that cumulative outdoor lux of 10,000 per day reduced risk of myopia onset compared with no outdoor exposure; simulation: compared with controls, 15-24% relative reduction in myopia would require 600,000-750,0000 outdoor lux/day or 120-150 outdoor min at 5,000 lux/min	some subject characteristics taken from X. He et al. (2019); as described under "IO-cut-off", the indoor/outdoor classification was realized via an SVM machine learning algorithm considering the variables lux, UV, and steps (Ye et al., 2019); yet, as the relationship between light intensity (lux) & myopia is analyzed – though split up indoor & outdoor light intensity –, the publication is listed here, and results on the association between time outdoors & myopia are also reported since they are often closely related to the results on light intensity & myopia, though it should be kept in mind that the indoor/outdoor distinction itself generally does not fall under the review's inclusion criteria

Supplementary Table C3 – Continued

Detailed Information About the Included Publications

S.-M. Li et al. (2022)	measurements excluded if illuminance value was fixed, (as this means the device has not been worn, because illuminance should fluctuate in normal use) recording time 7 AM-7 AM the following day *the analysis description indicates that all of the recording time was included in the analysis*	IO-cut-off: time outdoors defined as illuminance of ≥ 1,000 lux, citing other literature (Alvarez & Wildsoet, 2013; Dharani et al., 2012; Read et al., 2015)	among all children, negative correlation between axial elongation and time outdoors at weekends as well as time outdoors x light exposure, both at year 2 and 3, in linear regression analysis *(no information for year 1 and 4)* in mixed-effect models for outcomes AL & SER and parameters time (grade), group allocation, baseline outcomes, time outdoors & light exposure, the latter two n.s.	results (& many methods) of the intervention trial are not included here, as only the reported results on the correlation between device-measured light parameters and myopia metrics are within the review's scope

Note. The publications are sorted by the time when they were first published – publications published in the same month are sorted by the first author's name. [a]Relevant for lux measurements. [b]Only measurements relevant for the results and/or the respective refractive group classification reported; usually, more visual measurements were conducted. [c]Presented are demographics for the (sub)sample relevant for the results reported here – if no or only few information is given for this (sub)sample in the publication, the next largest (sub)sample is presented along with any information found on the (sub)sample relevant for said results. Generally, we report the overall number and main description of the subject sample as well as information on age, gender/sex, ethnicity, general visual information (including SER, but excluding AL specifications), information on the subject groups relevant for the reported results, and in- or exclusion criteria given in the publication. Often, the respective publications report more information about the subjects. [d]In a few cases, there might have been misplaced citations: (1) Contrary to what is stated, for some of the publications directly cited for light parameters and/or the IO-cut-off, we could not ascertain where a similar light meter or light measurements at all might have been used. (2) In case of light parameters having been adapted from elsewhere, we were not always able to identify where in the cited publications they were taken from. [e]In the publication, it says near work at this point, but based on overall context and other text passages, we suspect this to be a typo that should actually read LI. **Abbreviations:** AL = axial length. SER = spherical equivalent refraction.

D. Supplementary Material to Study 5

Supplementary Table D1

Means and Standard Deviations of Lux Measurements per Device per Day With Original Logging Rates

device	overall	indoors	outdoors
	day 1		
Actiwatch 2	1,337 (4,614)	757 (3,510)	2,675 (5,877)
Actiwatch Spectrum PRO	961 (6,490)	858 (7,596)	1,202 (2,425)
HOBO Pendant (collar)	6,152 (21,080)	869 (2,728)	18,342 (35,207)
HOBO Pendant (pedestal)	5,891 (15,983)	1,018 (4,841)	17,136 (24,690)
Clouclip M2	1,303 (3,239)	405 (835)	3,331 (5,166)
	day 2		
Actiwatch 2	867 (2,888)	261 (949)	2,220 (4,722)
Actiwatch Spectrum PRO	422 (728)	175 (295)	972 (1,040)
HOBO Pendant (collar)	7,101 (25,852)	899 (1,969)	20,950 (43,294)
HOBO Pendant (pedestal)	6,529 (23,741)	565 (1,439)	19,846 (39,509)
Vivior Monitor	714 (1,311)	154 (178)	1,965 (1,794)

Note. All values are given as mean (standard deviation). HOBO Pendant refers to HOBO Pendant UA-002-64.

Supplementary Table D2

Sensitivity and Specificity of the Environment Classification With the 1,000 Lux Cut-Off and Each Device's Determined Best Cut-Off With Original Logging Rates

	1,000 lux cut-off		best cut-off		
device	**sensitivity**	**specificity**	**cut-off (lux)**	**sensitivity**	**specificity**
day 1					
Actiwatch 2	48.2%	92.3%	420	78.2%	87.0%
Actiwatch Spectrum PRO	36.0%	92.3%	280	72.5%	76.8%
HOBO Pendant (collar)	94.4%	82.7%	1470	91.8%	91.9%
HOBO Pendant (pedestal)	96.3%	90.3%	1150	95.6%	91.4%
Clouclip M2	69.2%	92.8%	840	71.1%	91.5%
day 2					
Actiwatch 2	48.0%	97.8%	370	80.7%	85.9%
Actiwatch Spectrum PRO	35.7%	96.5%	310	71.5%	84.5%
HOBO Pendant (collar)	91.4%	73.2%	2590	82.7%	95.0%
HOBO Pendant (pedestal)	91.3%	79.7%	1900	86.2%	97.5%
Vivior Monitor	66.4%	99.8%	550	87.9%	95.6%

Note. The best cut-off was determined for each device and day by maximizing the sum of sensitivity and specificity via ROC curve analyses. HOBO Pendant refers to HOBO Pendant UA-002-64.

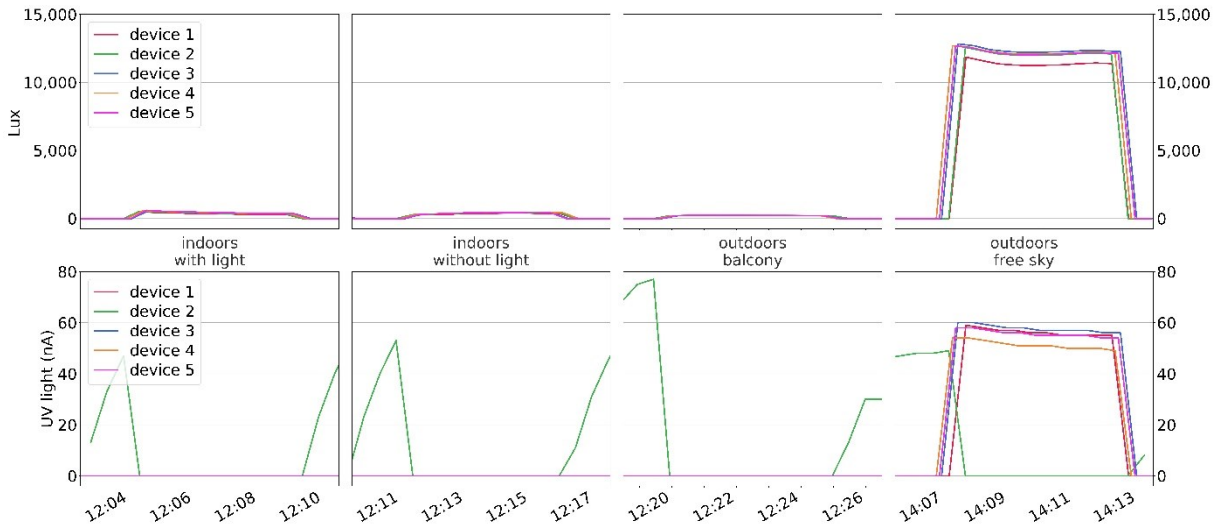
Supplementary Table D3

Sensitivity and Specificity of the Environment Classification of Each Device's Best Cut-Off for the Other Measurement Day With Original Logging Rates

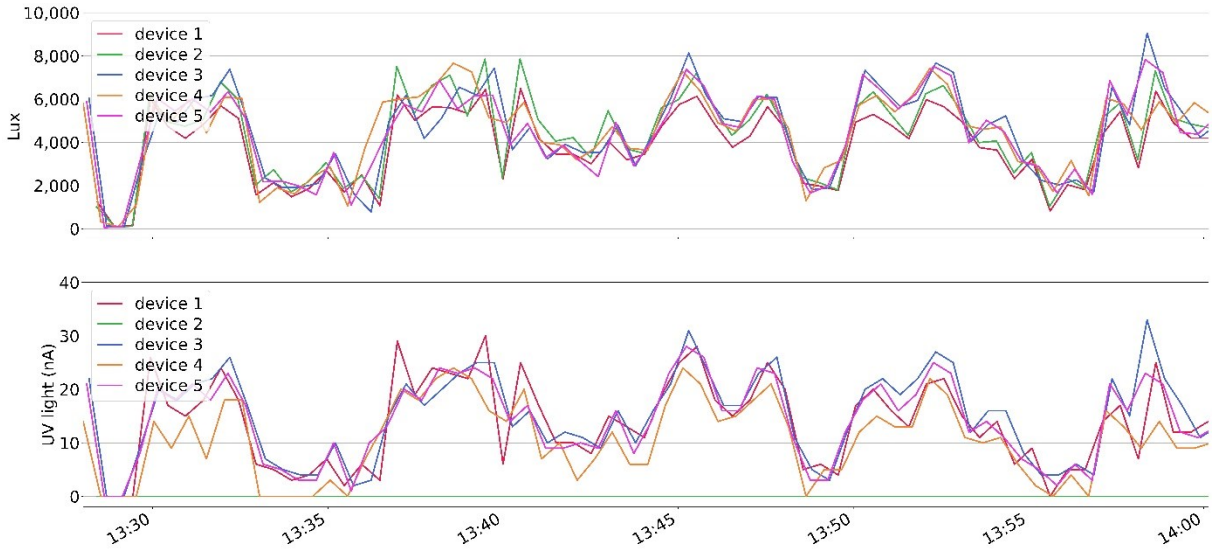
device	sensitivity	specificity
day 1 (classified with device's day 2 best cut-off)		
Actiwatch 2	83.7%	78.0%
Actiwatch Spectrum PRO	70.4%	78.5%
HOBO Pendant (collar)	85.5%	93.9%
HOBO Pendant (pedestal)	91.4%	92.9%
day 2 (classified with device's day 1 best cut-off)		
Actiwatch 2	74.0%	90.4%
Actiwatch Spectrum PRO	72.4%	83.2%
HOBO Pendant (collar)	88.0%	82.3%
HOBO Pendant (pedestal)	90.4%	84.2%

Note. HOBO Pendant refers to HOBO Pendant UA-002-64.

E. Supplementary Material to Study 6



Supplementary Figure E1. Lux and UV light data from the static device comparison measures plotted over time on a linear scale. The devices were covered with a black cloth prior and after each measurement. In the UV light measurements, the malfunction of device 2 is evident, as it always logged UV light measurement when the devices were covered, but not when they were not. Furthermore, a slight offset between the devices with regard to start and end of measurements can be seen, especially in the outdoors – free sky condition. This is due to the fact that their measurement times are not perfectly aligned. Due to the 30 s measuring interval, a between-device offset of up to 30 s is possible. Lastly, the time intervals between the individual plots (i.e., measurement conditions) vary, and there is a slight overlap between the first two plots since the respective measurements were taken in close temporal proximity.



Supplementary Figure E2. Lux and UV light data from the moving device comparison measurement plotted over time on a linear scale. In the UV light measurements, the malfunction of device 2 is evident in that it did not measure UV light at all. The (potential) malfunction of device 4 is also evident, as its UV light measurements dropped multiple times when those of the other devices did not.

F. Formalities

- Description of own contributions for Study 1
- Description of own contributions for Study 4
- Description of own contributions for Study 5
- Statement on ethical aspects and open science activities for Study 1
- Statement on ethical aspects and open science activities for Study 2
- Statement on ethical aspects and open science activities for Study 3
- Statement on ethical aspects and open science activities for Study 4
- Statement on ethical aspects and open science activities for Study 5
- Statement on ethical aspects and open science activities for Study 6

Description of Own Contributions for Study 1

Beschreibung der Eigenanteile des_der Doktorand_in an der Einzelarbeit mit weiteren CoAutor_innen:

Own contributions according to the CRediT taxonomy:
- Conceptualization
- Data curation
- Formal analysis
- Investigation
- Methodology
- Project administration
- Software
- Validation
- Visualization
- Writing – original draft
- Writing – review and editing

Wenn nötig, bitte zusätzliches Blatt verwenden.

Zur Erläuterung: Beispiele typischer Eigenaktivitäten

- Konzeption der Studien oder Experimente
- Erhebung, Analyse und Interpretation der Daten
- Erstellung des Manuskripts

Anmerkung: Diese Seite ist dem Anhang der Dissertation beizufügen.

Description of Own Contributions for Study 4

Beschreibung der Eigenanteile des_der Doktorand_in an der Einzelarbeit mit weiteren CoAutor_innen:

Own contributions according to the CRediT taxonomy:
- Conceptualization
- Data curation
- Formal analysis
- Investigation
- Methodology
- Project administration
- Validation
- Visualization
- Writing – original draft
- Writing – review and editing

Wenn nötig, bitte zusätzliches Blatt verwenden.

Zur Erläuterung: Beispiele typischer Eigenaktivitäten

- Konzeption der Studien oder Experimente
- Erhebung, Analyse und Interpretation der Daten
- Erstellung des Manuskripts

Anmerkung: Diese Seite ist dem Anhang der Dissertation beizufügen.

Description of Own Contributions for Study 5

Beschreibung der Eigenanteile des_der Doktorand_in an der Einzelarbeit mit weiteren CoAutor_innen:

Own contributions according to the CRediT taxonomy:
- Conceptualization
- Data curation
- Formal analysis
- Investigation
- Methodology
- Project administration
- Software
- Validation
- Visualization
- Writing – original draft
- Writing – review and editing

Wenn nötig, bitte zusätzliches Blatt verwenden.

Zur Erläuterung: Beispiele typischer Eigenaktivitäten

- Konzeption der Studien oder Experimente
- Erhebung, Analyse und Interpretation der Daten
- Erstellung des Manuskripts

Anmerkung: Diese Seite ist dem Anhang der Dissertation beizufügen.

Statement on Ethical Aspects and Open Science Activities for Study 1

Erklärung des_der Promovend_in zur Beschäftigung mit ethischen Aspekten und zur Dokumentation von Open Science-Aktivitäten im Rahmen der Promotion (für jede Einzelarbeit auszufüllen)

Promovend_in (Name, Vorname): Hönekopp, Astrid

Einzelarbeit (Titel):

Myopia Prevalence, Refractive Status and Uncorrected Myopia Among Primary and Secondary School Students in Germany

1. Beschäftigung mit ethischen Aspekten

In welcher Weise erfolgte eine Auseinandersetzung mit ethischen Aspekten im Rahmen der Planung und Durchführung der Studie?

Ethical aspects were considered all throughout the planning and conducting the study, including ensuring an non-invasive procedure that is as short and agreeable aspossible for the participants, informing the families regarding the study and the possibility to deny participation of their children, explaining all steps of the procedure to participants and answering their questions as well as ensuring immediate data anonymization. Not only the families, but also the (potential) participants themselves were given the option to deny or terminate their participation at any time and without stating a reason or experiencing disadvantages.

Wurde das Votum der Gemeinsamen Ethikkommission der Fakultäten 11 bis 17 der TU Dortmund (oder einer anderen Ethikkommission) eingeholt?

☒ ja

☐ nein, weil

2. Dokumentation von Open Science-Aktivitäten

	ja	nein	Wenn ja, bitte Quelle angeben
Präregistrierung		x	
Veröffentlichung von Daten		x	
Veröffentlichung von Auswertungsskripten		x	
Veröffentlichung von Materialien		x	
Open Access Publikation		x	
Preprint		x	

In dieser Einzelarbeit fanden Open Science-Aktivitäten keine/kaum Berücksichtigung, weil:

Since data acquisition was amidst the Covid 19-pandemic, we were not able to plan it ahead long enough to perform a pre-registration. Since the study is not published yet, neither are any scripts or materials. We do plan to publish Open Access, however, if the manuscript is accepted.

Statement on Ethical Aspects and Open Science Activities for Study 2

Erklärung des_der Promovend_in zur Beschäftigung mit ethischen Aspekten und zur Dokumentation von Open Science-Aktivitäten im Rahmen der Promotion (für jede Einzelarbeit auszufüllen)

Promovend_in (Name, Vorname): Hönekopp, Astrid

Einzelarbeit (Titel):

Participant Recruitment for Online Research – Lessons From a Parent Questionnaire Study on Children's Spectacle Ownership

1. Beschäftigung mit ethischen Aspekten

In welcher Weise erfolgte eine Auseinandersetzung mit ethischen Aspekten im Rahmen der Planung und Durchführung der Studie?

Questionnaire participants were informed about the aim and content of the questionnaire study prior participation and could terminate their participation at any time without stating a reason or negative consequences. The questionnaire data was acquired anonymously. Data from the voucher raffle participants could take part in were stored separately from the questionnaire data.

Wurde das Votum der Gemeinsamen Ethikkommission der Fakultäten 11 bis 17 der TU Dortmund (oder einer anderen Ethikkommission) eingeholt?

☒ ja

☐ nein, weil

2. Dokumentation von Open Science-Aktivitäten

	ja	nein	Wenn ja, bitte Quelle angeben
Präregistrierung		x	
Veröffentlichung von Daten		x	
Veröffentlichung von Auswertungsskripten		x	
Veröffentlichung von Materialien		x	
Open Access Publikation		x	
Preprint		x	

In dieser Einzelarbeit fanden Open Science-Aktivitäten keine/kaum Berücksichtigung, weil:

The study is not published or submitted for publication at the time of the submission of this dissertation, hence most of the open science activities do not apply. The study was not pre-registered since it was a subsequent analysis of metadata/additional data from Study 3.

Statement on Ethical Aspects and Open Science Activities for Study 3

Erklärung des_der Promovend_in zur Beschäftigung mit ethischen Aspekten und zur Dokumentation von Open Science-Aktivitäten im Rahmen der Promotion (für jede Einzelarbeit auszufüllen)

Promovend_in (Name, Vorname): Hönekopp, Astrid

Einzelarbeit (Titel):

Spectacle Ownership and Myopia in German Youth – Findings From Online Questionnaires and Their Relation to Refractive Data

1. Beschäftigung mit ethischen Aspekten

In welcher Weise erfolgte eine Auseinandersetzung mit ethischen Aspekten im Rahmen der Planung und Durchführung der Studie?

Questionnaire participants were informed about the aim and content of the questionnaire study prior participation and could terminate their participation at any time without stating a reason or negative consequences. The questionnaire data was acquired anonymously. Data from the voucher raffle participants could take part in were stored separately from the questionnaire data.

Wurde das Votum der Gemeinsamen Ethikkommission der Fakultäten 11 bis 17 der TU Dortmund (oder einer anderen Ethikkommission) eingeholt?

☒ ja

☐ nein, weil

2. Dokumentation von Open Science-Aktivitäten

	ja	nein	Wenn ja, bitte Quelle angeben
Präregistrierung		x	
Veröffentlichung von Daten		x	
Veröffentlichung von Auswertungsskripten		x	
Veröffentlichung von Materialien		x	
Open Access Publikation		x	
Preprint		x	

In dieser Einzelarbeit fanden Open Science-Aktivitäten keine/kaum Berücksichtigung, weil:

The study is not published or submitted for publication at the time of the submission of this dissertation, hence most of the open science activities do not apply. The study was not pre-registered due to its mainly descriptive nature.

Statement on Ethical Aspects and Open Science Activities for Study 4

Erklärung des_der Promovend_in zur Beschäftigung mit ethischen Aspekten und zur Dokumentation von Open Science-Aktivitäten im Rahmen der Promotion (für jede Einzelarbeit auszufüllen)

Promovend_in (Name, Vorname): Hönekopp, Astrid

Einzelarbeit (Titel):

Using Light Meters to Investigate the Light-Myopia Association – A Literature Review of Devices and Research Methods

1. Beschäftigung mit ethischen Aspekten

In welcher Weise erfolgte eine Auseinandersetzung mit ethischen Aspekten im Rahmen der Planung und Durchführung der Studie?

In planning the study, we considered if any ethical aspects needed to be taken into account. Since the study is a literature review and did not involve participants and only data already reported in other investigations, this was negated.

Wurde das Votum der Gemeinsamen Ethikkommission der Fakultäten 11 bis 17 der TU Dortmund (oder einer anderen Ethikkommission) eingeholt?

☐ ja

☒ nein, weil

The study is a literature review and does not involve participants, but analyzes data from other sources.

2. Dokumentation von Open Science-Aktivitäten

	ja	nein	Wenn ja, bitte Quelle angeben
Präregistrierung		x	
Veröffentlichung von Daten	x		The supplementary materials contain detailed information on the literature search and data of the investigations that were analyzed (https://doi.org/10.2147/OPTH.S420631).
Veröffentlichung von Auswertungsskripten		x	
Veröffentlichung von Materialien		x	
Open Access Publikation	x		
Preprint		x	

In dieser Einzelarbeit fanden Open Science-Aktivitäten keine/kaum Berücksichtigung, weil:

The literature review did not contain hypotheses and its specific focus evolved as the review process progressed. Thus, no preregistration was undertaken. Other than the description of the data published in the supplementary materials of the publication, there were no actual materials (or scripts) that could be published. As the study was published Open Access, we did not publish a preprint.

Statement on Ethical Aspects and Open Science Activities for Study 5

Erklärung des_der Promovend_in zur Beschäftigung mit ethischen Aspekten und zur Dokumentation von Open Science-Aktivitäten im Rahmen der Promotion (für jede Einzelarbeit auszufüllen)

Promovend_in (Name, Vorname): Hönekopp, Astrid

Einzelarbeit (Titel):

Comparing Simultaneously Worn Light Meters: Light Exposure Measurements, Indoor-Outdoor Distinctions and Implications for Myopia Research

1. Beschäftigung mit ethischen Aspekten

In welcher Weise erfolgte eine Auseinandersetzung mit ethischen Aspekten im Rahmen der Planung und Durchführung der Studie?

It was considered if there were any potential concerns with regard to study participation for myself as the participant wearing the devices, which was not the case. Participation was voluntary and could be stopped at any time.

Wurde das Votum der Gemeinsamen Ethikkommission der Fakultäten 11 bis 17 der TU Dortmund (oder einer anderen Ethikkommission) eingeholt?

☒ ja

☐ nein, weil

2. Dokumentation von Open Science-Aktivitäten

	ja	nein	Wenn ja, bitte Quelle angeben
Präregistrierung		X	
Veröffentlichung von Daten		X	
Veröffentlichung von Auswertungsskripten		X	
Veröffentlichung von Materialien		X	
Open Access Publikation		X	
Preprint		X	

In dieser Einzelarbeit fanden Open Science-Aktivitäten keine/kaum Berücksichtigung, weil:

The study is not published or submitted for publication at the time of the submission of this dissertation, hence most of the open science activities do not apply. The study was not preregistered due to its preliminary/small-scale nature.

Statement on Ethical Aspects and Open Science Activities for Study 6

Erklärung des_der Promovend_in zur Beschäftigung mit ethischen Aspekten und zur Dokumentation von Open Science-Aktivitäten im Rahmen der Promotion (für jede Einzelarbeit auszufüllen)

Promovend_in (Name, Vorname): Hönekopp, Astrid

Einzelarbeit (Titel):

A Feasibility Study on the Development of a Wearable Device for Investigating Light-Myopia Associations

1. Beschäftigung mit ethischen Aspekten

In welcher Weise erfolgte eine Auseinandersetzung mit ethischen Aspekten im Rahmen der Planung und Durchführung der Studie?

Ethical aspects were considered all throughout the planning and conducting the study: All steps of the procedure were explained to the participants and they were encouraged to ask questions throughout. Data was aqcuired and stored pseudonomously and only very few people were able to allocate the participants to the respective codes. Participants gave written consent prior participation and were able to terminate participation at any time without stating a reason or any negative consequences.

Wurde das Votum der Gemeinsamen Ethikkommission der Fakultäten 11 bis 17 der TU Dortmund (oder einer anderen Ethikkommission) eingeholt?

☒ ja

☐ nein, weil

2. Dokumentation von Open Science-Aktivitäten

	ja	nein	Wenn ja, bitte Quelle angeben
Präregistrierung		x	
Veröffentlichung von Daten		x	
Veröffentlichung von Auswertungsskripten		x	
Veröffentlichung von Materialien		x	
Open Access Publikation		x	
Preprint		x	

In dieser Einzelarbeit fanden Open Science-Aktivitäten keine/kaum Berücksichtigung, weil:

The study is not published or submitted for publication at the time of the submission of this dissertation, hence most of the open science activities do not apply. The study was not preregistered due to it being a feasibility study for a device development, thus being rather explorative in nature.

6. References

Aarts, M. P. J., van Duijnhoven, J., Aries, M. B. C., & Rosemann, A. L. P. (2017). Performance of personally worn dosimeters to study non-image forming effects of light: Assessment methods. *Building and Environment*, *117*, 60–72. https://doi.org/10.1016/j.buildenv.2017.03.002

Abbott, K. S., Queener, H. M., & Ostrin, L. A. (2018). The ipRGC-Driven Pupil Response with Light Exposure, Refractive Error, and Sleep. *Optometry and Vision Science*, *95*(4), 323–331. https://doi.org/10.1097/OPX.0000000000001198

Abboushi, B., Safranek, S., Rodriguez-Feo Bermudez, E., Pratoomratana, S., Chen, Y. [Yan], Poplawski, M., & Davis, R. (2022). A Review of the Use of Wearables in Indoor Environmental Quality Studies and an Evaluation of Data Accessibility from a Wearable Device. *Frontiers in Built Environment*, *8*, Article 787289. https://doi.org/10.3389/fbuil.2022.787289

Alsaif, B. A., Aljindan, M. Y., Alrammah, H. M., Almulla, M. O., & Alshahrani, S. S. (2019). Refractive errors among Saudi college students and associated risk factors. *Clinical Ophthalmology (Auckland, N.Z.)*, *13*, 437–443. https://doi.org/10.2147/OPTH.S193213

Alvarez, A. A. (2012). *Light, Nearwork, and Visual Environment Risk Factors in Myopia* [doctoral dissertation]. University of California, Berkeley. https://escholarship.org/uc/item/1bj5m20w

Alvarez, A. A., & Wildsoet, C. F. (2013). Quantifying light exposure patterns in young adult students. *Journal of Modern Optics*, *60*(14), 1200–1208. https://doi.org/10.1080/09500340.2013.845700

Alvarez-Peregrina, C. C., Sanchez-Tena, M. Á., Martinez-Perez, C., & Villa-Collar, C. (2019). Prevalence and Risk Factors of Myopia in Spain. *Journal of Ophthalmology*, *2019*, 3419576. https://doi.org/10.1155/2019/3419576

Alvarez-Peregrina, C. C., Sánchez-Tena, M. Á., Martinez-Perez, C., & Villa-Collar, C. (2020). The Relationship Between Screen and Outdoor Time With Rates of Myopia in Spanish Children. *Frontiers in Public Health*, *8*, 560378. https://doi.org/10.3389/fpubh.2020.560378

American Optometric Association. (n.d.). *Comprehensive Eye Exams*. Retrieved September 28, 2023, from https://www.aoa.org/healthy-eyes/caring-for-your-eyes/eye-exams?sso=y

Andrade, C. (2020). The Limitations of Online Surveys. *Indian Journal of Psychological Medicine*, *42*(6), 575–576. https://doi.org/10.1177/0253717620957496

Antonio-Aguirre, B., Emge, G., & Collins, M. (2023). Missed Vision Screenings for School-Age Children During The COVID-19 Pandemic: A Survey Based Study of NASN Representatives. *The Journal of School Nursing: The Official Publication of the National Association of School Nurses*, *39*(2), 156–161. https://doi.org/10.1177/10598405221117511

Antoun, C., Zhang, C., Conrad, F. G., & Schober, M. F. (2016). Comparisons of Online Recruitment Strategies for Convenience Samples. *Field Methods*, *28*(3), 231–246. https://doi.org/10.1177/1525822X15603149

Arcia, A. (2014). Facebook Advertisements for Inexpensive Participant Recruitment Among Women in Early Pregnancy. *Health Education & Behavior: The Official Publication of*

the Society for Public Health Education, *41*(3), 237–241. https://doi.org/10.1177/1090198113504414

Ashby, R. S., Ohlendorf, A., & Schaeffel, F. (2009). The effect of ambient illuminance on the development of deprivation myopia in chicks. *Investigative Ophthalmology & Visual Science*, *50*(11), 5348–5354. https://doi.org/10.1167/iovs.09-3419

Ashby, R. S., & Schaeffel, F. (2010). The effect of bright light on lens compensation in chicks. *Investigative Ophthalmology & Visual Science*, *51*(10), 5247–5253. https://doi.org/10.1167/iovs.09-4689

Atchison, D. A. (2009). Objective refraction. In M. Rosenfield & N. Logan (Eds.), *Optometry: Science, techniques, and clinical management* (2nd ed., pp. 187–208). Butterworth Heinemann.

Backhouse, S., Ng, H., & Phillips, J. (2011). Light Exposure Patterns in Children - A Pilot Study. In F. Schaeffel & M. Feldkaemper (Eds.), *Myopia: Proceedings of the 13th International Conference.* Optometry and Vision Science.

Baird, P. N., Saw, S.-M., Lanca, C., Guggenheim, J. A., Smith Iii, E. L., Zhou, X., Matsui, K.-O., Wu, P.-C. [Pei-Chang], Sankaridurg, P., Chia, A., Rosman, M., Lamoureux, E. L., Man, R., & He, M. (2020). Myopia. *Nature Reviews. Disease Primers*, *6*(1), 99. https://doi.org/10.1038/s41572-020-00231-4

Barry, J.-C. (2021). Approach Not Very Valid. *Deutsches Arzteblatt International*, *118*(17), 302. https://doi.org/10.3238/arztebl.m2021.0137

Bartón, K. (2023). *MuMIn: Multi-Model Inference* [Computer software]. https://cran.r-project.org/package=MuMIn

Bauldry, S. (2015). Structural Equation Modeling. In James D. Wright (Ed.), *International Encyclopedia of the Social & Behavioral Sciences* (pp. 615–620). Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.44055-9

Berra, S., Ravens-Sieberer, U., Erhart, M., Tebé, C., Bisegger, C., Duer, W., Rueden, U. von, Herdman, M., Alonso, J., & Rajmil, L. (2007). Methods and representativeness of a European survey in children and adolescents: The KIDSCREEN study. *BMC Public Health*, *7*, 182. https://doi.org/10.1186/1471-2458-7-182

Berufsverband der Augenärzte Deutschlands e.V., & Deutsche Ophthalmologische Gesellschaft e.V. (1998). *Leitlinie Nr. 4: Augenärztliche Basisdiagonstik bei Patienten ab dem 7. Lebensjahr* [Guideline No. 4: Basic ophthalmologic diagnostics for patients aged 7 years and older]. http://augeninfo.de/leit/leit04.htm

Berufsverband der Augenärzte Deutschlands e.V., & Deutsche Ophthalmologische Gesellschaft e.V. (2007). *Augenärzte informieren: Kinderbrillen* [Ophthalmologists inform: Children's glasses]. https://www.dog.org/wp-content/uploads/2009/11/Kinderbrillen-2007.pdf

Berufsverband der Augenärzte Deutschlands e.V., & Deutsche Ophthalmologische Gesellschaft e.V. (2010). *Leitlinie 26a Amblyopie* [Guideline 26a Amblyopia]. https://augeninfo.de/leit/leit26a.pdf

Bez, D., Megreli, J., Bez, M., Avramovich, E., Barak, A., & Levine, H. (2019). Association Between Type of Educational System and Prevalence and Severity of Myopia Among Male Adolescents in Israel. *JAMA Ophthalmology*, *137*(8), 887–893. https://doi.org/10.1001/jamaophthalmol.2019.1415

Bhandari, K. R., Mirhajianmoghadam, H., & Ostrin, L. A. (2021). Wearable Sensors for Measurement of Viewing Behavior, Light Exposure, and Sleep. *Sensors (Basel, Switzerland)*, *21*(21). https://doi.org/10.3390/s21217096

Bhandari, K. R., Shukla, D., Mirhajianmoghadam, H., & Ostrin, L. A. (2022). Objective Measures of Near Viewing and Light Exposure in Schoolchildren during COVID-19. *Optometry and Vision Science.* Advance online publication. https://doi.org/10.1097/OPX.0000000000001871

Biswas, S., Muralidharan, A. R., Betzler, B. K., Busoy, J. M. F., Barathi, V. A., Tan, R. K. Y., Low, W. Y. S., Milea, D., Kathrani, B. K., Brennan, N. A., & Najjar, R. P. (2023). A Duration-Dependent Interaction Between High-Intensity Light and Unrestricted Vision in the Drive for Myopia Control. *Investigative Ophthalmology & Visual Science*, *64*(3), 31. https://doi.org/10.1167/iovs.64.3.31

Blumenberg, C., Menezes, A. M. B., Gonçalves, H., Assunção, M. C. F., Wehrmeister, F. C., & Barros, A. J. D. (2019). How different online recruitment methods impact on recruitment rates for the web-based coortesnaweb project: A randomised trial. *BMC Medical Research Methodology*, *19*(1), 127. https://doi.org/10.1186/s12874-019-0767-z

Brainard, G. C., & Morgan, W. W. (1987). Light-induced stimulation of retinal dopamine: A dose-response relationship. *Brain Research*, *424*(1), 199–203. https://doi.org/10.1016/0006-8993(87)91211-x

Brennan, N. A., Toubouti, Y. M., Cheng, X., & Bullimore, M. A. (2021). Efficacy in myopia control. *Progress in Retinal and Eye Research*, *83*, 100923. https://doi.org/10.1016/j.preteyeres.2020.100923

Bruton, A., Conway, J. H., & Holgate, S. T. (2000). Reliability: What is it, and how is it measured? *Physiotherapy*, *86*(2), 94–99. https://doi.org/10.1016/S0031-9406(05)61211-4

Bullimore, M. A., Ritchey, E. R., Shah, S., Leveziel, N., Bourne, R. R. A., & Flitcroft, D. I. (2021). The Risks and Benefits of Myopia Control. *Ophthalmology*, *128*(11), 1561–1579. https://doi.org/10.1016/j.ophtha.2021.04.032

Burfield, H. J., Carkeet, A., & Ostrin, L. A. (2019). Ocular and Systemic Diurnal Rhythms in Emmetropic and Myopic Adults. *Investigative Ophthalmology & Visual Science*, *60*(6), 2237–2247. https://doi.org/10.1167/iovs.19-26711

Calvano, C., Engelke, L., Di Bella, J., Kindermann, J., Renneberg, B., & Winter, S. M. (2022). Families in the COVID-19 pandemic: Parental stress, parent mental health and the occurrence of adverse childhood experiences-results of a representative survey in Germany. *European Child & Adolescent Psychiatry*, *31*(7), 1–13. https://doi.org/10.1007/s00787-021-01739-0

Campbell, C. E., Benjamin, W. J., & Howland, H. C. (2006). Objective Refraction: Retinoscopy, Autorefraction, and Photorefraction. In W. J. Benjamin (Ed.), *Borish's Clinical Refraction* (2nd ed., pp. 682–764). Butterworth Heinemann.

Choy, B. N. K., You, Q., Zhu, M. M., Lai, J. S. M., Ng, A. L. K., & Wong, I. Y. H. (2020). Prevalence and associations of myopia in Hong Kong primary school students. *Japanese Journal of Ophthalmology*, *64*(4), 437–449. https://doi.org/10.1007/s10384-020-00733-4

Cohn, H. (1886). *The hygiene of the eye in schools*. Simpkin & Marshall Co.

Congdon, N., Burnett, A., & Frick, K. (2019). The impact of uncorrected myopia on individuals and society. *Community Eye Health*, *32*(105), 7–8.

Cosic, I., Cosic, D., & Lazar, K. (2016). Environmental Light and Its Relationship with Electromagnetic Resonances of Biomolecular Interactions, as Predicted by the Resonant Recognition Model. *International Journal of Environmental Research and Public Health*, *13*(7). https://doi.org/10.3390/ijerph13070647

Crowne, D. P., & Marlowe, D. (1960). A new scale of social desirability independent of psychopathology. *Journal of Consulting Psychology*, *24*, 349–354. https://doi.org/10.1037/h0047358

Cuellar-Partida, G., Lu, Y. [Yi], Kho, P. F., Hewitt, A. W., Wichmann, H.-E., Yazar, S., Stambolian, D., Bailey-Wilson, J. E., Wojciechowski, R., Wang, J. J., Mitchell, P., Mackey, D. A., & MacGregor, S. (2016). Assessing the Genetic Predisposition of Education on Myopia: A Mendelian Randomization Study. *Genetic Epidemiology*, *40*(1), 66–72. https://doi.org/10.1002/gepi.21936

Cui, D., Trier, K., & Munk Ribel-Madsen, S. (2013). Effect of day length on eye growth, myopia progression, and change of corneal power in myopic children. *Ophthalmology*, *120*(5), 1074–1079. https://doi.org/10.1016/j.ophtha.2012.10.022

Czepita, M., Czepita, D., & Safranow, K. (2019). Role of Gender in the Prevalence of Myopia among Polish Schoolchildren. *Journal of Ophthalmology*, *2019*, 9748576. https://doi.org/10.1155/2019/9748576

Dhakal, R., Rudrapankte, J. R., Chittajallu, H. S. N. S., Lawrenson, J. G., Huntjens, B., Shah, R., & Verkicharla, P. K. (2023). Development and validation of a 'MyLyt' wearable light tracking device. *Ophthalmic and Physiological Optics*, *43*(1), 132–140. https://doi.org/10.1111/opo.13061

Dharani, R., Lee, C.-F., Finkelstein, E. A., & Saw, S.-M. (2013). Response to Mahroo et al. *Eye*, *27*(8), 991. https://doi.org/10.1038/eye.2013.89

Dharani, R., Lee, C.-F., Theng, Z. X., Drury, V. B., Ngo, C., Sandar, M., Wong, T.-Y., Finkelstein, E. A., & Saw, S.-M. (2012). Comparison of measurements of time outdoors and light levels as risk factors for myopia in young Singapore children. *Eye (London, England)*, *26*(7), 911–918. https://doi.org/10.1038/eye.2012.49

Ding, B.-Y., Shih, Y.-F., Lin, L. L. K., Hsiao, C. K., & Wang, I.-J. (2017). Myopia among schoolchildren in East Asia and Singapore. *Survey of Ophthalmology*, *62*(5), 677–697. https://doi.org/10.1016/j.survophthal.2017.03.006

Dirani, M., Tong, L., Gazzard, G., Zhang, X., Chia, A., Young, T. L., Rose, K. A., Mitchell, P., & Saw, S.-M. (2009). Outdoor activity and myopia in Singapore teenage children. *The British Journal of Ophthalmology*, *93*(8), 997–1000. https://doi.org/10.1136/bjo.2008.150979

Dolgin, E. (2015). The myopia boom. *Nature*, *519*(7543), 276–278. https://doi.org/10.1038/519276a

Dong, L., Kang, Y. K., Li, Y. [Yang], Wei, W. B., & Jonas, J. B. (2020). Prevalence and Time Trends of Myopia in Children and Adolescents in China: A Systemic Review and Meta-Analysis. *Retina (Philadelphia, Pa.)*, *40*(3), 399–411. https://doi.org/10.1097/IAE.0000000000002590

Donovan, L., Sankaridurg, P., Ho, A., Chen, X., Lin, Z. [Zhi], Thomas, V., Smith, E. L., Ge, J., & Holden, B. (2012). Myopia progression in Chinese children is slower in summer

than in winter. *Optometry and Vision Science*, *89*(8), 1196–1202. https://doi.org/10.1097/OPX.0b013e3182640996

Dudovitz, R. N., Izadpanah, N., Chung, P. J., & Slusser, W. (2016). Parent, Teacher, and Student Perspectives on How Corrective Lenses Improve Child Wellbeing and School Function. *Maternal and Child Health Journal*, *20*(5), 974–983. https://doi.org/10.1007/s10995-015-1882-z

Duran, M., & Cevher, S. (2023). Effect of cycloplegic agents (1% cyclopentolate hydrochloride and 1% tropicamide) on anterior segment parameters. *Therapeutic Advances in Ophthalmology*, *15*, 25158414231180984. https://doi.org/10.1177/25158414231180984

Dworkin, J., Hessel, H., Gliske, K., & Rudi, J. H. (2016). A Comparison of Three Online Recruitment Strategies for Engaging Parents. *Family Relations*, *65*(4), 550–561. https://doi.org/10.1111/fare.12206

Elston, D. M. (2021). Participation bias, self-selection bias, and response bias. *Journal of the American Academy of Dermatology.* Advance online publication. https://doi.org/10.1016/j.jaad.2021.06.025

Emerson, R. W. (2020). Regression Analysis and Adjusted R2. *Journal of Visual Impairment & Blindness*, *114*(4), 332–333. https://doi.org/10.1177/0145482X20939786

Enaholo, E. S., Musa, M. J., & Zeppieri, M. (2024). *StatPearls: Objective Refraction Technique: Retinoscopy.*

Eppenberger, L. S., & Sturm, V. (2020). The Role of Time Exposed to Outdoor Light for Myopia Prevalence and Progression: A Literature Review. *Clinical Ophthalmology (Auckland, N.Z.)*, *14*, 1875–1890. https://doi.org/10.2147/OPTH.S245192

Esaki, Y., Kitajima, T., Obayashi, K., Saeki, K., Fujita, K., & Iwata, N. (2019). Daytime light exposure in daily life and depressive symptoms in bipolar disorder: A cross-sectional analysis in the APPLE cohort. *Journal of Psychiatric Research*, *116*, 151–156. https://doi.org/10.1016/j.jpsychires.2019.06.010

Fan, Y., Liao, J., Liu, S. [Shichun], Cai, X., Lv, S., Yang, Q., Dong, Y., Li, H. [Hua], & Song, S. (2022). Effect of Time Outdoors and Near-viewing Time on Myopia Progression in 9- to 11-year-old Children in Chongqing. *Optometry and Vision Science*, *99*(6), 489–495. https://doi.org/10.1097/OPX.0000000000001898

Feldmann, A., Gasser, O., Lichtblau, F., Pujol, E., Poese, I., Dietzel, C., Wagner, D., Wichtlhuber, M., Tapiador, J., Vallina-Rodriguez, N., Hohlfeld, O., & Smaragdakis, G. (2020). The Lockdown Effect. In *Proceedings of the ACM Internet Measurement Conference* (pp. 1–18). ACM. https://doi.org/10.1145/3419394.3423658

Figueiro, M. G., Hamner, R., Bierman, A., & Rea, M. S. (2013). Comparisons of three practical field devices used to measure personal light exposures and activity levels. *Lighting Research & Technology (London, England : 2001)*, *45*(4), 421–434. https://doi.org/10.1177/1477153512450453.

Finger, R. P., & Schuster, A. K. (2019). Myopie in Deutschland – Veränderungen der Prävalenz bleiben unklar [Myopia in Germany – changes in the prevalence remain unclear]. *Der Ophthalmologe: Zeitschrift der Deutschen Ophthalmologischen Gesellschaft*, *116*(7), 682–683. https://doi.org/10.1007/s00347-019-0915-1

Flanagan, S. C., Cobice, D., Richardson, P., Sittlington, J. J., & Saunders, K. J. (2020). Elevated Melatonin Levels Found in Young Myopic Adults Are Not Attributable to a

Shift in Circadian Phase. *Investigative Ophthalmology & Visual Science*, *61*(8), 45. https://doi.org/10.1167/iovs.61.8.45

Flitcroft, D. I. (2012). The complex interactions of retinal, optical and environmental factors in myopia aetiology. *Progress in Retinal and Eye Research*, *31*(6), 622–660. https://doi.org/10.1016/j.preteyeres.2012.06.004

Flitcroft, D. I., He, M., Jonas, J. B., Jong, M., Naidoo, K., Ohno-Matsui, K., Rahi, J., Resnikoff, S., Vitale, S., & Yannuzzi, L. (2019). Imi - Defining and Classifying Myopia: A Proposed Set of Standards for Clinical and Epidemiologic Studies. *Investigative Ophthalmology & Visual Science*, *60*(3), M20-M30. https://doi.org/10.1167/iovs.18-25957

Flynn, J. I., Coe, D. P., Larsen, C. A., Rider, B. C., Conger, S. A., & Bassett, D. R. (2014). Detecting indoor and outdoor environments using the ActiGraph GT3X+ light sensor in children. *Medicine and Science in Sports and Exercise*, *46*(1), 201–206. https://doi.org/10.1249/MSS.0b013e3182a388c0

Fogel-Levin, M., Doron, R., Wygnanski-Jaffe, T., Ancri, O., & Ben Zion, I. (2016). A comparison of plusoptiX A12 measurements with cycloplegic refraction. *Journal of AAPOS : The Official Publication of the American Association for Pediatric Ophthalmology and Strabismus*, *20*(4), 310–314. https://doi.org/10.1016/j.jaapos.2016.04.006

Foster, P. J., & Jiang, Y. (2014). Epidemiology of myopia. *Eye (London, England)*, *28*(2), 202–208. https://doi.org/10.1038/eye.2013.280

Fotedar, R., Rochtchina, E., Morgan, I., Wang, J. J., Mitchell, P., & Rose, K. A. (2007). Necessity of cycloplegia for assessing refractive error in 12-year-old children: A population-based study. *American Journal of Ophthalmology*, *144*(2), 307–309. https://doi.org/10.1016/j.ajo.2007.03.041

Franklin, K. J. (2020). *The effects of environment and lifestyle on eye growth* [doctoral dissertation]. Aston University, Birmingham. https://research.aston.ac.uk/files/50335689/FRANKLIN_KATHERINE_JAYNE_104871423

French, A. N., Ashby, R. S., Morgan, I. G., & Rose, K. A. (2013). Time outdoors and the prevention of myopia. *Experimental Eye Research*, *114*, 58–68. https://doi.org/10.1016/j.exer.2013.04.018

Gao, Z., Meng, N., Muecke, J., Chan, W. O., Piseth, H., Kong, A., Jnguyenphamhh, T., Dehghan, Y., Selva, D., Casson, R., & Ang, K. (2012). Refractive error in school children in an urban and rural setting in Cambodia. *Ophthalmic Epidemiology*, *19*(1), 16–22. https://doi.org/10.3109/09286586.2011.632703

Genicom Co., Ltd. (2018). *UV-A Sensor: GUVA-S12SD* (Rev. 1.0).

Germine, L., Nakayama, K., Duchaine, B. C., Chabris, C. F., Chatterjee, G., & Wilmer, J. B. (2012). Is the Web as good as the lab? Comparable performance from Web and lab in cognitive/perceptual experiments. *Psychonomic Bulletin & Review*, *19*(5), 847–857. https://doi.org/10.3758/s13423-012-0296-9

Ghadimi, H., Nikdel, M., & Suh, D. W. (2024). Comparison of photorefraction by Plusoptix A12 and cycloplegic autorefraction in children. *BMC Ophthalmology*, *24*(1), 179. https://doi.org/10.1186/s12886-024-03459-w

Gilmartin, B. (2004). Myopia: Precedents for research in the twenty-first century. *Clinical & Experimental Ophthalmology*, *32*(3), 305–324. https://doi.org/10.1111/j.1442-9071.2004.00831.x

Gordon-Shaag, A., Shneor, E., Doron, R., Levine, J., & Ostrin, L. A. (2021). Environmental and Behavioral Factors with Refractive Error in Israeli Boys. *Optometry and Vision Science*, *98*(8), 959–970. https://doi.org/10.1097/OPX.0000000000001755

Gosling, S. D., Sandy, C. J., John, O. P., & Potter, J. (2010). Wired but not WEIRD: The promise of the Internet in reaching more diverse samples. *The Behavioral and Brain Sciences*, *33*(2-3), 94–95. https://doi.org/10.1017/S0140525X10000300

Gosling, S. D., Vazire, S., Srivastava, S., & John, O. P. (2004). Should we trust web-based studies? A comparative analysis of six preconceptions about internet questionnaires. *The American Psychologist*, *59*(2), 93–104. https://doi.org/10.1037/0003-066X.59.2.93

Grzybowski, A., Kanclerz, P., Tsubota, K., Lanca, C., & Saw, S.-M. (2020). A review on the epidemiology of myopia in school children worldwide. *BMC Ophthalmology*, *20*(1), 27. https://doi.org/10.1186/s12886-019-1220-0

Guggenheim, J. A., Northstone, K., McMahon, G., Ness, A. R., Deere, K., Mattocks, C., Pourcain, B. S., & Williams, C. (2012). Time Outdoors and Physical Activity as Predictors of Incident Myopia in Childhood: A Prospective Cohort Study. *Investigative Ophthalmology & Visual Science*, *53*(6), 2856–2865. https://doi.org/10.1167/iovs.11-9091

Guo, Y., Liu, L. J., Xu, L. [Liang], Tang, P., Lv, Y. Y., Feng, Y., Meng, M., & Jonas, J. B. (2013). Myopic shift and outdoor activity among primary school children: One-year follow-up study in Beijing. *PloS One*, *8*(9), e75260. https://doi.org/10.1371/journal.pone.0075260

GWI. (2020). *Welche der folgenden Aktivitäten haben Sie aufgrund des Coronavirus zu Hause durchgeführt?* [Which of the following activities have you carried out at home due to the coronavirus?]. https://de.statista.com/statistik/daten/studie/1110746/umfrage/veraenderung-des-konsums-digitaler-medien-waehrend-der-corona-krise/

Gwiazda, J., Deng, L., Manny, R., & Norton, T. T. (2014). Seasonal variations in the progression of myopia in children enrolled in the correction of myopia evaluation trial. *Investigative Ophthalmology & Visual Science*, *55*(2), 752–758. https://doi.org/10.1167/iovs.13-13029

Hagen, L. A., Gjelle, J. V. B., Arnegard, S., Pedersen, H. R., Gilson, S. J., & Baraas, R. C. (2018). Prevalence and Possible Factors of Myopia in Norwegian Adolescents. *Scientific Reports*, *8*(1), 13479. https://doi.org/10.1038/s41598-018-31790-y

Hangzhou JingZhiJing Technology Co. Ltd. (n.d.). *CLOUCLIP: Myopia Related Behavioral Control - Smart Device - Big Data.*

Harb, E. N., Chan, M., Tran, A., & Wildsoet, C. F. (2016). Characteristics of Indoor and Outdoor Light Exposure Differ With Refractive Status in Young Adults. *Investigative Ophthalmology & Visual Science*, *57*(12), ARVO E-Abstract 2473. https://iovs.arvojournals.org/article.aspx?articleid=2560910

Harrington, S. C., Stack, J., & O'Dwyer, V. (2019). Risk factors associated with myopia in schoolchildren in Ireland. *The British Journal of Ophthalmology*, *103*(12), 1803–1809. https://doi.org/10.1136/bjophthalmol-2018-313325

Harrington, S. C., Stack, J., Saunders, K., & O'Dwyer, V. (2019). Refractive error and visual impairment in Ireland schoolchildren. *The British Journal of Ophthalmology*, *103*(8), 1112–1118. https://doi.org/10.1136/bjophthalmol-2018-312573

Hartmeyer, S. L., Webler, F. S., & Andersen, M. (2022). Towards a framework for light-dosimetry studies: Methodological considerations. *Lighting Research & Technology (London, England: 2001)*, 147715352211032. https://doi.org/10.1177/14771535221103258

Hashemi, H., Khabazkhoob, M., Asharlous, A., Soroush, S., Yekta, A., Dadbin, N., & Fotouhi, A. (2016). Cycloplegic autorefraction versus subjective refraction: The Tehran Eye Study. *The British Journal of Ophthalmology*, *100*(8), 1122–1127. https://doi.org/10.1136/bjophthalmol-2015-307871

Havas Media. (2020). *Welche digitale Medien haben Sie in der letzten Woche (viel) mehr benutzt?* [Which digital media have you used (much) more in the last week?]. https://de.statista.com/statistik/daten/studie/1121090/umfrage/nutzung-von-digitalen-medien-waehrend-der-corona-krise/

He, M., Xiang, F., Zeng, Y., Mai, J., Chen, Q., Zhang, J., Smith, W., Rose, K., & Morgan, I. G. (2015). Effect of Time Spent Outdoors at School on the Development of Myopia Among Children in China: A Randomized Clinical Trial. *JAMA*, *314*(11), 1142–1148. https://doi.org/10.1001/jama.2015.10803

He, X [Xiangui], Sankaridurg, P., Wang, J. [Jingjing], Chen, J. [Jun], Naduvilath, T., He, M., Zhu, Z., Li, W., Morgan, I. G., Xiong, S., Zhu, J., Zou, H., Rose, K. A., Zhang, B., Weng, R., Resnikoff, S., & Xu, X. (2022). Time Outdoors in Reducing Myopia: A School-Based Cluster Randomized Trial with Objective Monitoring of Outdoor Time and Light Intensity. *Ophthalmology*, *129*(11), 1245–1254. https://doi.org/10.1016/j.ophtha.2022.06.024

He, X. [Xiangui], Sankaridurg, P., Xiong, S., Li, W., Zhang, B., Weng, R., Zhu, J., Naduvilath, T., Resnikoff, S., Zou, H., & Xu, X. (2019). Shanghai Time Outside to Reduce Myopia trial: Design and baseline data. *Clinical & Experimental Ophthalmology*, *47*(2), 171–178. https://doi.org/10.1111/ceo.13391

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *The Behavioral and Brain Sciences*, *33*(2-3), 61-135. https://doi.org/10.1017/S0140525X0999152X

Ho, C.-L., Wu, W.-F., & Liou, Y. M. (2019). Dose-Response Relationship of Outdoor Exposure and Myopia Indicators: A Systematic Review and Meta-Analysis of Various Research Methods. *International Journal of Environmental Research and Public Health*, *16*(14). https://doi.org/10.3390/ijerph16142595

Hoffmann, R., Lange, M., Butschalowsky, H., Houben, R., Schmich, P., Allen, J., Kuhnert, R., Schaffrath Rosario, A., & Großwald, A. (2018). Querschnitterhebung von KiGGS Welle 2 – Teilnehmendengewinnung, Response und Repräsentativität [Cross-sectional survey of KiGGS wave 2 – participant recruitment, response and representativeness]. *Journal of Health Monitoring*, *3*(1), 82–95. https://doi.org/10.17886/RKI-GBE-2018-015

Hofmarcher, T. (2021). The effect of education on poverty: A European perspective. *Economics of Education Review*, *83*, 102124. https://doi.org/10.1016/j.econedurev.2021.102124

Holden, B. A., Fricke, T. R., Wilson, D. A., Jong, M., Naidoo, K. S., Sankaridurg, P., Wong, T. Y., Naduvilath, T. J., & Resnikoff, S. (2016). Global Prevalence of Myopia and High Myopia and Temporal Trends from 2000 through 2050. *Ophthalmology*, *123*(5), 1036–1042. https://doi.org/10.1016/j.ophtha.2016.01.006

Holden, B. A., Sankaridurg, P., Smith, E., Aller, T., Jong, M., & He, M. (2014). Myopia, an underrated global challenge to vision: Where the current data takes us on myopia control. *Eye (London, England)*, *28*(2), 142–146. https://doi.org/10.1038/eye.2013.256

Hollis, J., Allen, P. M., & Heywood, J. (2022). Learning retinoscopy: A journey through problem space. *Ophthalmic and Physiological Optics*, *42*(5), 940–947. https://doi.org/10.1111/opo.13007

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, *6*, 65-70. https://www.jstor.org/stable/4615733

Hönekopp, A., & Weigelt, S. (2023). Using Light Meters to Investigate the Light-Myopia Association – A Literature Review of Devices and Research Methods. *Clinical Ophthalmology (Auckland, N.Z.)*, *17*, 2737–2760. https://doi.org/10.2147/OPTH.S420631

Hopkins, S., Narayanasamy, S., Vincent, S. J., Sampson, G. P., & Wood, J. M. (2020). Do reduced visual acuity and refractive error affect classroom performance? *Clinical & Experimental Optometry*, *103*(3), 278–289. https://doi.org/10.1111/cxo.12953

Howell, C. M., McCullough, S. J., Doyle, L., Murphy, M. H., & Saunders, K. J. (2021). Reliability and validity of the Actiwatch and Clouclip for measuring illumination in real-world conditions. *Ophthalmic and Physiological Optics*, *41*(5), 1048–1059. https://doi.org/10.1111/opo.12860

International Commission on Illumination. (n.d.–a). *17-659*. https://cie.co.at/eilv/659

International Commission on Illumination. (n.d.–b). *E-ILV: 17-21-003*. https://cie.co.at/eilvterm/17-21-003

International Commission on Illumination. (n.d.–c). *E-ILV: 17-21-004*. Retrieved February 16, 2024, from https://cie.co.at/eilvterm/17-21-004

International Commission on Illumination. (n.d.–d). *E-ILV: 17-21-008*. https://cie.co.at/eilvterm/17-21-008

International Commission on Illumination. (n.d.–e). *E-ILV: 17-21-035*. https://cie.co.at/eilvterm/17-21-035

International Commission on Illumination. (n.d.–f). *E-ILV: 17-21-038*. https://cie.co.at/eilvterm/17-21-038

International Commission on Illumination. (n.d.–g). *E-ILV: 17-21-053*. https://cie.co.at/eilvterm/17-21-053

International Commission on Illumination. (n.d.–h). *E-ILV: 17-21-056*. https://cie.co.at/eilvterm/17-21-056

International Commission on Illumination. (n.d.–i). *E-ILV: 17-22-002*. https://cie.co.at/eilvterm/17-22-002

International Commission on Illumination. (n.d.–j). *E-ILV: 17-22-003*. https://cie.co.at/eilvterm/17-22-003

International Commission on Illumination. (n.d.–k). *E-ILV: 17-22-016*. https://cie.co.at/eilvterm/17-22-016

International Commission on Illumination. (n.d.–l). *E-ILV: 17-22-017*. https://cie.co.at/eilvterm/17-22-017

Iuvone, P. M., Galli, C. L., Garrison-Gund, C. K., & Neff, N. H. (1978). Light stimulates tyrosine hydroxylase activity and dopamine synthesis in retinal amacrine neurons. *Science (New York, N.Y.)*, *202*(4370), 901–902. https://doi.org/10.1126/science.30997

IvenSense Inc. (2013). *MPU-6000/MPU6050 Product Specification* (Revision 3.4).

Jardim, A. C. N., Pawley, M. D. M., Cheeseman, J. F., Guesgen, M. J., Steele, C. T., & Warman, G. R. (2011). Validating the use of wrist-level light monitoring for in-hospital circadian studies. *Chronobiology International*, *28*(9), 834–840. https://doi.org/10.3109/07420528.2011.611603

Jobke, S., Kasten, E., & Vorwerk, C. (2008). The prevalence rates of refractive errors among children, adolescents, and adults in Germany. *Clinical Ophthalmology (Auckland, N.Z.)*, *2*(3), 601–607. https://doi.org/10.2147/opth.s2836

Jones, L. A., Sinnott, L. T., Mutti, D. O., Mitchell, G. L., Moeschberger, M. L., & Zadnik, K. (2007). Parental history of myopia, sports and outdoor activities, and future myopia. *Investigative Ophthalmology & Visual Science*, *48*(8), 3524–3532. https://doi.org/10.1167/iovs.06-1118

Joyce, D. S., Zele, A. J., Feigl, B., & Adhikari, P. (2020). The accuracy of artificial and natural light measurements by actigraphs. *Journal of Sleep Research*, *29*(5), e12963. https://doi.org/10.1111/jsr.12963

Kaduk, T., Goeke, C., Finger, H., & König, P. (2023). Webcam eye tracking close to laboratory standards: Comparing a new webcam-based system and the EyeLink 1000. *Behavior Research Methods.* Advance online publication. https://doi.org/10.3758/s13428-023-02237-8

Karouta, C., & Ashby, R. S. (2015). Correlation between light levels and the development of deprivation myopia. *Investigative Ophthalmology & Visual Science*, *56*(1), 299–309. https://doi.org/10.1167/iovs.14-15499

Karthikeyan, S. K., Ashwini, D. L., Priyanka, M., Nayak, A., & Biswas, S. (2022). Physical activity, time spent outdoors, and near work in relation to myopia prevalence, incidence, and progression: An overview of systematic reviews and meta-analyses. *Indian Journal of Ophthalmology*, *70*(3), 728–739. https://doi.org/10.4103/ijo.IJO_1564_21

Kaur, K., & Gurnani, B. (2024). *StatPearls: Subjective Refraction Techniques.*

Kaymak, H., Neller, K., Funk, S., Langenbucher, A., Seitz, B., & Schwahn, H. (2022). Optometrische Schulreihenuntersuchungen: Erste Ergebnisse eines Pilotprojekts zur logistischen Machbarkeit [Optometric eye screening in schools: First results of a pilot project on logistical feasibility]. *Der Ophthalmologe: Zeitschrift der Deutschen Ophthalmologischen Gesellschaft*, *119*(Suppl 1), 25–32. https://doi.org/10.1007/s00347-021-01394-5

Kemper, A. R., Cohn, L. M., & Dombkowski, K. J. (2004). Patterns of vision care among Medicaid-enrolled children. *Pediatrics*, *113*(3 Pt 1), e190-6. https://doi.org/10.1542/peds.113.3.e190

Klijs, B., Scholtens, S., Mandemakers, J. J., Snieder, H., Stolk, R. P., & Smidt, N. (2015). Representativeness of the LifeLines Cohort Study. *PloS One*, *10*(9), e0137203. https://doi.org/10.1371/journal.pone.0137203

Koninklijke Philips N.V. (n.d.–a). *Actiwatch 2 - Activity Monitor*. Retrieved August 15, 2022, from https://www.usa.philips.com/healthcare/product/HC1044809/actiwatch-2-activity-monitor

Koninklijke Philips N.V. (n.d.–b). *Actiwatch Spectrum - Activity Monitor*. Retrieved September 26, 2022, from https://www.usa.philips.com/healthcare/product/HC1046964/actiwatch-spectrum-activity-monitor

Koninklijke Philips N.V. (n.d.–c). *Actiwatch Spectrum Plus - Get the Actiwatch advantage*. Retrieved September 28, 2022, from https://www.usa.philips.com/healthcare/product/HCNOCTN445/actiwatch-spectrum-plus-get-the-actiwatch-advantage

Koninklijke Philips N.V. (2008). *Characterization of Light Sensor Performance for Three Models of Actiwatch: Actiwatch-64, Actiwatch 2 and Actiwatch Spectrum*. http://www.actigraphy.respironics.com/assets/ActiwatchLightSensorPerformance-71c44d6474b549abcd85a903695855d6989fa3d8b2c5aa046bd972289f716fd8.pdf

Koninklijke Philips N.V. (2013). *Professional sleep and activity monitoring solutions: Actiwatch monitoring systems*. https://www.documents.philips.com/assets/20200915/5937512f9a6e49af9d0aac370112bcod.pdf

Koo, T. K., & Li, M. Y. (2016). A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research. *Journal of Chiropractic Medicine*, *15*(2), 155–163. https://doi.org/10.1016/j.jcm.2016.02.012

Krantz, E. M., Cruickshanks, K. J., Klein, B. E. K., Klein, R., Huang, G.-H., & Nieto, F. J. (2010). Measuring refraction in adults in epidemiological studies. *Archives of Ophthalmology (Chicago, Ill.: 1960)*, *128*(1), 88–92. https://doi.org/10.1001/archophthalmol.2009.349

Lagrèze, W. A., & Schaeffel, F. (2017). Preventing Myopia. *Deutsches Arzteblatt International*, *114*(35-36), 575–580. https://doi.org/10.3238/arztebl.2017.0575

Landis, E. G., Yang, V., Brown, D. M., Pardue, M. T., & Read, S. A. (2018). Dim Light Exposure and Myopia in Children. *Investigative Ophthalmology & Visual Science*, *59*(12), 4804–4811. https://doi.org/10.1167/iovs.18-24415

Landmann, A., & Bechrakis, E. (2013). Anlage versus Umwelt: Wie stark sind Ametropien angeboren? [Nature or nurture: effects of parental ametropia on children's refractive errors]. *Der Ophthalmologe: Zeitschrift der Deutschen Ophthalmologischen Gesellschaft*, *110*(12), 1179–1184. https://doi.org/10.1007/s00347-013-2782-5

Leighton, K., Kardong-Edgren, S., Schneidereith, T., & Foisy-Doll, C. (2021). Using Social Media and Snowball Sampling as an Alternative Recruitment Strategy for Research. *Clinical Simulation in Nursing*, *55*, 37–42. https://doi.org/10.1016/j.ecns.2021.03.006

Li, L., Wen, L., Lan, W., Zhu, H., & Yang, Z. (2020). A Novel Approach to Quantify Environmental Risk Factors of Myopia: Combination of Wearable Devices and Big Data Science. *Translational Vision Science & Technology*, *9*(13), 17. https://doi.org/10.1167/tvst.9.13.17

Li, L., Zhu, H., Wen, L., Lan, W., & Yang, Z. (2021). An Approach of Combining Convolution Neural Network and Graph Convolution Network to Predict the Progression of

Myopia. *Neural Processing Letters.* Advance online publication. https://doi.org/10.1007/s11063-021-10576-w

Li, M., Lanca, C., Tan, C.-S., Foo, L.-L., Sun, C.-H., Yap, F., Najjar, R. P., Sabanayagam, C., & Saw, S.-M. (2021). Association of time outdoors and patterns of light exposure with myopia in children. *The British Journal of Ophthalmology.* Advance online publication. https://doi.org/10.1136/bjophthalmol-2021-318918

Li, S.-M., Ran, A.-R., Kang, M.-T., Yang, X., Ren, M.-Y., Wei, S.-F., Gan, J.-H., Li, L., He, X. [Xi], Li, H. [He], Liu, L.-R., Wang, Y., Zhan, S.-Y., Atchison, D. A., Morgan, I., & Wang, N. (2022). Effect of Text Messaging Parents of School-Aged Children on Outdoor Time to Control Myopia: A Randomized Clinical Trial. *JAMA Pediatrics*, *176*(11), 1077–1083. https://doi.org/10.1001/jamapediatrics.2022.3542

Lin, L. L. K., Shih, Y. F., Hsiao, C. K., & Chen, C. J. (2004). Prevalence of myopia in Taiwanese schoolchildren: 1983 to 2000. *Annals of the Academy of Medicine, Singapore*, *33*(1), 27–33.

Lin, Z. [Zhong], Gao, T. Y., Vasudevan, B., Ciuffreda, K. J., Liang, Y. B., Jhanji, V., Fan, S. J., Han, W., & Wang, N. L. (2017). Near work, outdoor activity, and myopia in children in rural China: The Handan offspring myopia study. *BMC Ophthalmology*, *17*(1), 203. https://doi.org/10.1186/s12886-017-0598-9

Lingham, G., Mackey, D. A., Lucas, R., & Yazar, S. (2020). How does spending time outdoors protect against myopia? A review. *The British Journal of Ophthalmology*, *104*(5), 593–599. https://doi.org/10.1136/bjophthalmol-2019-314675

Liu, L., Marler, M. R., Parker, B. A., Jones, V., Johnson, S., Cohen-Zion, M., Fiorentino, L., Sadler, G. R., & Ancoli-Israel, S. (2005). The relationship between fatigue and light exposure during chemotherapy. *Supportive Care in Cancer: Official Journal of the Multinational Association of Supportive Care in Cancer*, *13*(12), 1010–1017. https://doi.org/10.1007/s00520-005-0824-5

Liu, S. [Sam], Coulter, R., Sui, W., Nuss, K., & Rhodes, R. E. (2023). Determinants of recreational screen time behavior following the COVID-19 pandemic among Canadian adults. *Applied Physiology, Nutrition, and Metabolism*, *48*(8), 595–602. https://doi.org/10.1139/apnm-2022-0379

Liu, Z., Pazo, E. E., Ye, H., Yu, C., Xu, L. [Ling], & He, W. (2021). Comparing School-Aged Refraction Measurements Using the 2WIN-S Portable Refractor in Relation to Cycloplegic Retinoscopy: A Cross-Sectional Study. *Journal of Ophthalmology*, *2021*, 6612476. https://doi.org/10.1155/2021/6612476

Logan, N. S., & Wolffsohn, J. S. (2020). Role of un-correction, under-correction and over-correction of myopia as a strategy for slowing myopic progression. *Clinical & Experimental Optometry*, *103*(2), 133–137. https://doi.org/10.1111/cxo.12978

Lundberg, K., Suhr Thykjaer, A., Søgaard Hansen, R., Vestergaard, A. H., Jacobsen, N., Goldschmidt, E., Lima, R. A., Peto, T., Wedderkopp, N., & Grauslund, J. (2018). Physical activity and myopia in Danish children-The CHAMPS Eye Study. *Acta Ophthalmologica*, *96*(2), 134–141. https://doi.org/10.1111/aos.13513

Ma, X., Zhou, Z., Yi, H., Pang, X., Shi, Y., Chen, Q., Meltzer, M. E., Le Cessie, S., He, M., Rozelle, S., Liu, Y., & Congdon, N. (2014). Effect of providing free glasses on children's educational outcomes in China: Cluster randomized controlled trial. *BMJ (Clinical Research Ed.)*, *349*, g5740. https://doi.org/10.1136/bmj.g5740

Ma, Y., Congdon, N., Shi, Y., Hogg, R., Medina, A., Boswell, M., Rozelle, S., & Iyer, M. (2018). Effect of a Local Vision Care Center on Eyeglasses Use and School Performance in Rural China: A Cluster Randomized Clinical Trial. *JAMA Ophthalmology*, *136*(7), 731–737. https://doi.org/10.1001/jamaophthalmol.2018.1329

Maaravi, Y., & Heller, B. (2020). Not all worries were created equal: The case of COVID-19 anxiety. *Public Health*, *185*, 243–245. https://doi.org/10.1016/j.puhe.2020.06.032

Mahroo, O. A., Gavin, E. A., Williams, K. M., Smit, E. de, Hammond, C. J., & Morrison, D. A. (2013). Potential effect of 'cut-off intensity' on correlation between light meter measurements and time outdoors. *Eye*, *27*(8), 990–991. https://doi.org/10.1038/eye.2013.88

Markvart, J., Hansen, Å. M., & Christoffersen, J. (2015). Comparison and Correction of the Light Sensor Output from 48 Wearable Light Exposure Devices by Using a Side-by-Side Field Calibration Method. *LEUKOS*, *11*(3), 155–171. https://doi.org/10.1080/15502724.2015.1020948

Matamoros, E., Ingrand, P., Pelen, F., Bentaleb, Y., Weber, M., Korobelnik, J.-F., Souied, E., & Leveziel, N. (2015). Prevalence of Myopia in France: A Cross-Sectional Analysis. *Medicine*, *94*(45), e1976. https://doi.org/10.1097/MD.0000000000001976

McCarthy, C. S., Megaw, P., Devadas, M., & Morgan, I. G. (2007). Dopaminergic agents affect the ability of brief periods of normal vision to prevent form-deprivation myopia. *Experimental Eye Research*, *84*(1), 100–107. https://doi.org/10.1016/j.exer.2006.09.018

McGraw, K. O., & Wong, S. P. (1996). Forming inferences about some intraclass correlation coefficients. *Psychological Methods*, *1*(1), 30–46. https://doi.org/10.1037/1082-989X.1.1.30

Mirhajianmoghadam, H., Piña, A., & Ostrin, L. A. (2021). Objective and Subjective Behavioral Measures in Myopic and Non-Myopic Children During the COVID-19 Pandemic. *Translational Vision Science & Technology*, *10*(11), 4. https://doi.org/10.1167/tvst.10.11.4

Mirshahi, A., Ponto, K. A., Hoehn, R., Zwiener, I., Zeller, T., Lackner, K., Beutel, M. E., & Pfeiffer, N. (2014). Myopia and level of education: Results from the Gutenberg Health Study. *Ophthalmology*, *121*(10), 2047–2052. https://doi.org/10.1016/j.ophtha.2014.04.017

Moafa, M. A. M. (2019). *Quantifying Risk Factors for Myopia: Instrument Validation and Establishing Dosage for Light Intensity and Duration* [doctoral dissertation]. The University of Sydney, Sydney. https://ses.library.usyd.edu.au/bitstream/handle/2123/21273/MOAFA_MA_THESIS.pdf

Morgan, I. G., Ashby, R. S., & Nickla, D. L. (2013). Form deprivation and lens-induced myopia: Are they different? *Ophthalmic and Physiological Optics*, *33*(3), 355–361. https://doi.org/10.1111/opo.12059

Morgan, I. G., French, A. N., Ashby, R. S., Guo, X., Ding, X., He, M., & Rose, K. A. (2018). The epidemics of myopia: Aetiology and prevention. *Progress in Retinal and Eye Research*, *62*, 134–149. https://doi.org/10.1016/j.preteyeres.2017.09.004

Morgan, I. G., Ohno-Matsui, K., & Saw, S.-M. (2012). Myopia. *The Lancet*, *379*(9827), 1739–1748. https://doi.org/10.1016/S0140-6736(12)60272-4

Morgan, I. G., & Rose, K. (2005). How genetic is school myopia? *Progress in Retinal and Eye Research*, *24*(1), 1–38. https://doi.org/10.1016/j.preteyeres.2004.06.004

Morgan, I. G., Wu, P.-C. [Pei-Chang], Ostrin, L. A., Tideman, J. W. L., Yam, J. C., Lan, W., Baraas, R. C., He, X. [Xiangui], Sankaridurg, P., Saw, S.-M., French, A. N., Rose, K. A., & Guggenheim, J. A. (2021). IMI Risk Factors for Myopia. *Investigative Ophthalmology & Visual Science*, *62*(5), 3. https://doi.org/10.1167/iovs.62.5.3

Mountjoy, E., Davies, N. M., Plotnikov, D., Smith, G. D., Rodriguez, S., Williams, C. E., Guggenheim, J. A., & Atan, D. (2018). Education and myopia: Assessing the direction of causality by mendelian randomisation. *BMJ (Clinical Research Ed.)*, *361*, k2022. https://doi.org/10.1136/bmj.k2022

Muralidharan, A. R., Lança, C., Biswas, S., Barathi, V. A., Low, S. W. Y., Saw, S.-M., Milea, D., & Najjar, R. P. (2021). Light and myopia: From epidemiological studies to neurobiological mechanisms. *Therapeutic Advances in Ophthalmology*, *13*, 25158414211059246. https://doi.org/10.1177/25158414211059246

Mutti, D. O., Mitchell, G. L., Moeschberger, M. L., Jones, L. A., & Zadnik, K. (2002). Parental Myopia, Near Work, School Achievement, and Children's Refractive Error. *Investigative Ophthalmology & Visual Science*, *43*(12), 3633–3640.

Myrowitz, E. H. (2012). Juvenile myopia progression, risk factors and interventions. *Saudi Journal of Ophthalmology: Official Journal of the Saudi Ophthalmological Society*, *26*(3), 293–297. https://doi.org/10.1016/j.sjopt.2011.03.002

Nagra, M., Rodriguez-Carmona, M., Blane, S., & Huntjens, B. (2021). Intra- and Inter-Model Variability of Light Detection Using a Commercially Available Light Sensor. *Journal of Medical Systems*, *45*(4), 46. https://doi.org/10.1007/s10916-020-01694-4

Naidoo, K. S., Fricke, T. R., Frick, K. D., Jong, M., Naduvilath, T. J., Resnikoff, S., & Sankaridurg, P. (2019). Potential Lost Productivity Resulting from the Global Burden of Myopia: Systematic Review, Meta-analysis, and Modeling. *Ophthalmology*, *126*(3), 338–346. https://doi.org/10.1016/j.ophtha.2018.10.029

Nishanth, S., Manoharan, K., Srinivasan, M., Vidhyalakshmi, S., Gouvindasamy, K., Bauer, N., & Berendschot, T. T. (2022). Accurate measurement of outdoor activities in children with myopia: Development of an affordable wearable device. *Investigative Ophthalmology & Visual Science*, *63*(7), 2144 – A0172. https://iovs.arvojournals.org/article.aspx?articleid=2780565

O'Donoghue, L., McClelland, J. F., Logan, N. S., Rudnicka, A. R., Owen, C. G., & Saunders, K. J. (2010). Refractive error and visual impairment in school children in Northern Ireland. *The British Journal of Ophthalmology*, *94*(9), 1155–1159. https://doi.org/10.1136/bjo.2009.176040

Ohno, Y., Goodman, T., Blattner, P., Schanda, J., Shitomi, H., Sperling, A., & Zwinkels, J. (2020). Principles governing photometry (2nd edition). *Metrologia*, *57*(2), 20401. https://doi.org/10.1088/1681-7575/ab72f1

Onset Computer Corporation. (2012). *HOBO® Pendant Temperature/Light Data Logger (Part # UA-002-XX)* (Doc # 9556-I, MAN-UA-002).

Ostrin, L. A. (2017). Objectively Measured Light Exposure in Emmetropic and Myopic Adults. *Optometry and Vision Science*, *94*(2), 229–238. https://doi.org/10.1097/OPX.0000000000001013

Ostrin, L. A. (2018). The ipRGC-driven pupil response with light exposure and refractive error in children. *Ophthalmic and Physiological Optics*, *38*(5), 503–515. https://doi.org/10.1111/opo.12583

Ostrin, L. A., Abbott, K. S., & Queener, H. M. (2017). Attenuation of short wavelengths alters sleep and the ipRGC pupil response. *Ophthalmic and Physiological Optics*, *37*(4), 440–450. https://doi.org/10.1111/opo.12385

Ostrin, L. A., Jnawali, A., Carkeet, A., & Patel, N. B. (2019). Twenty-four hour ocular and systemic diurnal rhythms in children. *Ophthalmic and Physiological Optics*, *39*(5), 358–369. https://doi.org/10.1111/opo.12633

Ostrin, L. A., Read, S. A., Vincent, S. J., & Collins, M. J. (2020). Sleep in Myopic and Non-Myopic Children. *Translational Vision Science & Technology*, *9*(9), 22. https://doi.org/10.1167/tvst.9.9.22

Ostrin, L. A., Sajjadi, A., & Benoit, J. S. (2018). Objectively Measured Light Exposure During School and Summer in Children. *Optometry and Vision Science*, *95*(4), 332–342. https://doi.org/10.1097/OPX.0000000000001208

Pajic, B., Zakharov, P., Pajic-Eggspuehler, B., & Cvejic, Z. (2020). User Friendliness of a Wearable Visual Behavior Monitor for Cataract and Refractive Surgery. *Applied Sciences*, *10*(6), 2190. https://doi.org/10.3390/app10062190

Pärssinen, O., & Lyyra, A.-L. (1993). Myopia and myopic progression among schoolchildren: a three-year follow-up study. *Investigative Ophthalmology & Visual Science*, *34*(9), 2794–2802.

Pascolini, D., & Mariotti, S. P. (2012). Global estimates of visual impairment: 2010. *The British Journal of Ophthalmology*, *96*(5), 614–618. https://doi.org/10.1136/bjophthalmol-2011-300539

Payerols, A., Eliaou, C., Trezeguet, V., Villain, M., & Daien, V. (2016). Accuracy of PlusOptix A09 distance refraction in pediatric myopia and hyperopia. *BMC Ophthalmology*, *16*, 72. https://doi.org/10.1186/s12886-016-0247-8

Pedersen, E. R., Helmuth, E. D., Marshall, G. N., Schell, T. L., PunKay, M., & Kurz, J. (2015). Using facebook to recruit young adult veterans: Online mental health research. *JMIR Research Protocols*, *4*(2), e63. https://doi.org/10.2196/resprot.3996

Perry, B., Herrington, W., Goldsack, J. C., Grandinetti, C. A., Vasisht, K. P., Landray, M. J., Bataille, L., DiCicco, R. A., Bradley, C., Narayan, A., Papadopoulos, E. J., Sheth, N., Skodacek, K., Stem, K., Strong, T. V., Walton, M. K., & Corneli, A. (2018). Use of Mobile Devices to Measure Outcomes in Clinical Research, 2010-2016: A Systematic Literature Review. *Digital Biomarkers*, *2*(1), 11–30. https://doi.org/10.1159/000486347

Phan, L. (2022). *Myopia Research: Improving the Quantificaton of Risk Factors* [doctoral dissertation]. University of Technology Sydney, Sydney. http://hdl.handle.net/10453/170514

Plusoptix GmbH. (2009). *Pediatric Autorefractor plusoptiX A09 Bedienungsanleitung* [Pediatric autorefractor plusoptiX A09 user manual]. https://www.plusoptix.com/fileadmin/Downloads/Products/Eye_care_product_models/A09/Plusoptix_A09_user-manual_de.pdf

Plusoptix GmbH. (2020). *Gerätemodell-Vergleich* [Device model comparison]. https://www.plusoptix.com/fileadmin/Downloads/Geraetemodell-Vergleiche/Plusoptix_Geraetemodell-Vergleich_Autorefractor_de.pdf

Popović-Beganović, A., Zvorničanin, J., Vrbljanac, V., & Zvorničanin, E. (2018). The Prevalence of Refractive Errors and Visual Impairment among School Children in Brčko District, Bosnia and Herzegovina. *Seminars in Ophthalmology*, *33*(7-8), 858–868. https://doi.org/10.1080/08820538.2018.1539182

Prepas, S. B. (2008). Light, literacy and the absence of ultraviolet radiation in the development of myopia. *Medical Hypotheses*, *70*(3), 635–637. https://doi.org/10.1016/j.mehy.2007.07.023

PwC. (2020). *Welche Medienkanäle haben Sie während der Corona-Krise vermehrt benutzt und wie wahrscheinlich ist es, dass die gestiegene Nutzung beibehalten wird?* [Which media channels did you use more often during the coronavirus crisis and how likely is it that this increased usage will continue?]. https://de.statista.com/statistik/daten/studie/1127564/umfrage/nutzung-von-medienkanaelen-waehrend-der-corona-krise/

Qiu, M., Wang, S. Y., Singh, K., & Lin, S. C. (2014). Racial disparities in uncorrected and undercorrected refractive error in the United States. *Investigative Ophthalmology & Visual Science*, *55*(10), 6996–7005. https://doi.org/10.1167/iovs.13-12662

R Core Team. (2021). *R: A language and environment for statistical computing* [Computer software]. R Foundation for Statistical Computing. Vienna, Austria. https://www.R-project.org/

Read, S. A., Collins, M. J., & Vincent, S. J. (2014). Light exposure and physical activity in myopic and emmetropic children. *Optometry and Vision Science*, *91*(3), 330–341. https://doi.org/10.1097/OPX.0000000000000160

Read, S. A., Collins, M. J., & Vincent, S. J. (2015). Light Exposure and Eye Growth in Childhood. *Investigative Ophthalmology & Visual Science*, *56*(11), 6779–6787. https://doi.org/10.1167/iovs.14-15978

Read, S. A., Pieterse, E. C., Alonso-Caneiro, D., Bormann, R., Hong, S., Lo, C.-H., Richer, R., Syed, A., & Tran, L. (2018). Daily morning light therapy is associated with an increase in choroidal thickness in healthy young adults. *Scientific Reports*, *8*(1), 8200. https://doi.org/10.1038/s41598-018-26635-7

Read, S. A., Vincent, S. J., Tan, C.-S., Ngo, C., Collins, M. J., & Saw, S.-M. (2018). Patterns of Daily Outdoor Light Exposure in Australian and Singaporean Children. *Translational Vision Science & Technology*, *7*(3), 8. https://doi.org/10.1167/tvst.7.3.8

Refinetti, R. (2019). Chronotype Variability and Patterns of Light Exposure of a Large Cohort of United States Residents. *The Yale Journal of Biology and Medicine*, *92*(2), 179–186.

Reimers, S., & Stewart, N. (2015). Presentation and response timing accuracy in Adobe Flash and HTML5/JavaScript Web experiments. *Behavior Research Methods*, *47*(2), 309–327. https://doi.org/10.3758/s13428-014-0471-1

Revelle, W. (2021). *psych: Procedures for Personality and Psychological Research* (Version 2.1.9) [Computer software]. Northwestern University. Evanston, Illinois, USA. https://CRAN.R-project.org/package=psych

ROHM Co., Ltd. (2014). *Digital 16bit Serial Output Type Ambient Light Sensor IC: BH1750FVI* (Rev. 001).

Rohrer, B., Spira, A. W., & Stell, W. K. (1993). Apomorphine blocks form-deprivation myopia in chickens by a dopamine D2-receptor mechanism acting in retina or pigmented

epithelium. *Visual Neuroscience*, *10*(3), 447–453. https://doi.org/10.1017/s0952523800004673

Rose, K. A., French, A. N., & Morgan, I. G. (2016). Environmental Factors and Myopia: Paradoxes and Prospects for Prevention. *Asia-Pacific Journal of Ophthalmology (Philadelphia, Pa.)*, *5*(6), 403–410. https://doi.org/10.1097/APO.0000000000000233

Rose, K. A., Morgan, I. G., Ip, J., Kifley, A., Huynh, S., Smith, W., & Mitchell, P. (2008). Outdoor activity reduces the prevalence of myopia in children. *Ophthalmology*, *115*(8), 1279–1285. https://doi.org/10.1016/j.ophtha.2007.12.019

Rose, K. A., Morgan, I. G., Smith, W., Burlutsky, G., Mitchell, P., & Saw, S.-M. (2008). Myopia, lifestyle, and schooling in students of Chinese ethnicity in Singapore and Sydney. *Archives of Ophthalmology (Chicago, Ill.: 1960)*, *126*(4), 527–530. https://doi.org/10.1001/archopht.126.4.527

Rose, K. A., Smith, W., Morgan, I., & Mitchell, P. (2001). The increasing prevalence of myopia: Implications for Australia. *Clinical & Experimental Ophthalmology*, *29*(3), 116–120. https://doi.org/10.1046/j.1442-9071.2001.00389.x

Rosenfield, M. (2009). Subjective refraction. In M. Rosenfield & N. Logan (Eds.), *Optometry: Science, techniques, and clinical management* (2nd ed., pp. 209–228). Butterworth Heinemann.

RStudio Team. (2021). *RStudio: Integrated Development Environment for R* [Computer software]. RStudio, PCB. Boston, MA. http://www.rstudio.com

Rudnicka, A. R., Kapetanakis, V. V., Wathern, A. K., Logan, N. S., Gilmartin, B., Whincup, P. H., Cook, D. G., & Owen, C. G. (2016). Global variations and time trends in the prevalence of childhood myopia, a systematic review and quantitative meta-analysis: Implications for aetiology and early prevention. *The British Journal of Ophthalmology*, *100*(7), 882–890. https://doi.org/10.1136/bjophthalmol-2015-307724

Sanfilippo, P. G., Chu, B.-S., Bigault, O., Kearns, L. S., Boon, M.-Y., Young, T. L., Hammond, C. J., Hewitt, A. W., & Mackey, D. A. (2014). What is the appropriate age cut-off for cycloplegia in refraction? *Acta Ophthalmologica*, *92*(6), e458-62. https://doi.org/10.1111/aos.12388

Sankaridurg, P., Tahhan, N., Kandel, H., Naduvilath, T., Zou, H., Frick, K. D., Marmamula, S., Friedman, D. S., Lamoureux, E., Keeffe, J., Walline, J. J., Fricke, T. R., Kovai, V., & Resnikoff, S. (2021). IMI Impact of Myopia. *Investigative Ophthalmology & Visual Science*, *62*(5), 2. https://doi.org/10.1167/iovs.62.5.2

Saw, S.-M., Gazzard, G., Shih-Yen, E. C., & Chua, W.-H. (2005). Myopia and associated pathological complications. *Ophthalmic and Physiological Optics*, *25*(5), 381–391. https://doi.org/10.1111/j.1475-1313.2005.00298.x

Saw, S.-M., Zhang, X., & Pu, S.-H. (2015). *Device to prevent a condition or disease associated with a lack of outdoor time.* (WO2015152818A1). World Intellectual Property Organization. https://patentimages.storage.googleapis.com/e0/db/03/89d1027735c6e5/WO2015152818A1.pdf

Scheuermaier, K., Laffan, A. M., & Duffy, J. F. (2010). Light exposure patterns in healthy older and young adults. *Journal of Biological Rhythms*, *25*(2), 113–122. https://doi.org/10.1177/0748730410361916

Schmid, K. L., Leyden, K., Chiu, Y., Lind, S.-R., Vos, D. J., Kimlin, M., & Wood, J. M. (2013). Assessment of daily light and ultraviolet exposure in young adults. *Optometry and Vision Science*, *90*(2), 148–155. https://doi.org/10.1097/OPX.0b013e31827cda5b

Schräpler, J. P., & Jeworutzki, S. (2021). *Konstruktion des Sozialindex für Schulen in Nordrhein-Westfalen: ZEFIR-Materialien Band 14* [Construction of the social index for schools in North Rhine-Westphalia: ZEFIR-Materials Volume 14]. Zentrum für interdisziplinäre Regionalforschung.

Schuster, A. K. (2021). In Reply. *Deutsches Arzteblatt International*, *118*(17), 302. https://doi.org/10.3238/arztebl.m2021.0138

Schuster, A. K., Krause, L., Kuchenbäcker, C., Prütz, F., Elflein, H. M., Pfeiffer, N., & Urschitz, M. S. (2020). Prevalence and Time Trends in Myopia Among Children and Adolescents. *Deutsches Arzteblatt International*, *117*(50), 855–860. https://doi.org/10.3238/arztebl.2020.0855

Semmelmann, K., Hönekopp, A., & Weigelt, S. (2017). Looking Tasks Online: Utilizing Webcams to Collect Video Data from Home. *Frontiers in Psychology*, *8*, 1582. https://doi.org/10.3389/fpsyg.2017.01582

Semmelmann, K., & Weigelt, S. (2017). Online psychophysics: Reaction time effects in cognitive experiments. *Behavior Research Methods*, *49*(4), 1241–1260. https://doi.org/10.3758/s13428-016-0783-4

Semmelmann, K., & Weigelt, S. (2018). Online webcam-based eye tracking in cognitive science: A first look. *Behavior Research Methods*, *50*(2), 451–465. https://doi.org/10.3758/s13428-017-0913-7

Senthilkumar, D., Balasubramaniam, S. M., Kumaran, S. E., & Ramani, K. K. (2013). Parents' awareness and perception of children's eye diseases in Chennai, India. *Optometry and Vision Science*, *90*(12), 1462–1466. https://doi.org/10.1097/OPX.0000000000000084

Shickle, D., & Farragher, T. M. (2015). Geographical inequalities in uptake of NHS-funded eye examinations: Small area analysis of Leeds, UK. *Journal of Public Health (Oxford, England)*, *37*(2), 337–345. https://doi.org/10.1093/pubmed/fdu039

Shickle, D., Farragher, T. M., Davey, C. J., Slade, S. V., & Syrett, J. (2018). Geographical inequalities in uptake of NHS funded eye examinations: Poisson modelling of small-area data for Essex, UK. *Journal of Public Health (Oxford, England)*, *40*(2), e171-e179. https://doi.org/10.1093/pubmed/fdx058

Shneor, E., Doron, R., Levine, J., Zimmerman, D. R., Benoit, J. S., Ostrin, L. A., & Gordon-Shaag, A. (2021). Objective Behavioral Measures in Children before, during, and after the COVID-19 Lockdown in Israel. *International Journal of Environmental Research and Public Health*, *18*(16). https://doi.org/10.3390/ijerph18168732

Singh, S., & Sagar, R. (2021). A critical look at online survey or questionnaire-based research studies during COVID-19. *Asian Journal of Psychiatry*, *65*, 102850. https://doi.org/10.1016/j.ajp.2021.102850

Slavin, R. E., Collins, M. E., Repka, M. X., Friedman, D. S., Mudie, L. I., Owoeye, J. O., & Madden, N. A. (2018). In Plain Sight: Reading Outcomes of Providing Eyeglasses to Disadvantaged Children. *Journal of Education for Students Placed at Risk (JESPAR)*, *23*(3), 250–258. https://doi.org/10.1080/10824669.2018.1477602

Sliney, D. H. (2016). What is light? The visible spectrum and beyond. *Eye (London, England)*, *30*(2), 222–229. https://doi.org/10.1038/eye.2015.252

Smith, E. L., Hung, L.-F., Arumugam, B., & Huang, J. (2013). Negative lens-induced myopia in infant monkeys: Effects of high ambient lighting. *Investigative Ophthalmology & Visual Science*, *54*(4), 2959–2969. https://doi.org/10.1167/iovs.13-11713

Smith, E. L., Hung, L.-F., & Huang, J. (2012). Protective effects of high ambient lighting on the development of form-deprivation myopia in rhesus monkeys. *Investigative Ophthalmology & Visual Science*, *53*(1), 421–428. https://doi.org/10.1167/iovs.11-8652

Spillmann, L. (2020). Stopping the rise of myopia in Asia. *Graefe's Archive for Clinical and Experimental Ophthalmology*, *258*(5), 943–959. https://doi.org/10.1007/s00417-019-04555-0

Statistisches Bundesamt. (2023a). *Altersstruktur der Bevölkerung in Deutschland zum 31. Dezember 2022* [Age structure of the population in Germany as of December 31, 2022]. https://de.statista.com/statistik/daten/studie/1351/umfrage/altersstruktur-der-bevoelkerung-deutschlands/

Statistisches Bundesamt. (2023b). *Anzahl der Familien mit Kindern unter 18 Jahren in Deutschland nach Kinderanzahl im Jahr 2022* [Number of families with children under 18 in Germany by number of children in 2022]. https://de.statista.com/statistik/daten/studie/71320/umfrage/anzahl-der-familien-mit-kindern-unter-18-jahren-in-deutschland-nach-kinderzahl/

Statistisches Bundesamt. (2023c). *Bevölkerung - Verteilung der Männer und Frauen in Deutschland nach relevanten Altersgruppen am 31. Dezember 2022* [Population - distribution of men and women in Germany by relevant age groups as of December 31, 2022]. https://de.statista.com/statistik/daten/studie/828264/umfrage/maenner-und-frauen-in-deutschland-nach-altersgruppen/

Statistisches Bundesamt. (2023d). *Bevölkerung nach Nationalität und Geschlecht (Quartalszahlen)* [Population by nationality and gender (quarterly figures)]. https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/Tabellen/liste-zensus-geschlecht-staatsangehoerigkeit.html#616584

Stewart, N., Chandler, J., & Paolacci, G. (2017). Crowdsourcing Samples in Cognitive Science. *Trends in Cognitive Sciences*, *21*(10), 736–748. https://doi.org/10.1016/j.tics.2017.06.007

Stone, R. A., Pardue, M. T., Iuvone, P. M., & Khurana, T. S. (2013). Pharmacology of myopia and potential role for intrinsic retinal circadian rhythms. *Experimental Eye Research*, *114*, 35–47. https://doi.org/10.1016/j.exer.2013.01.001

Strang, N. C., Schmid, K. L., & Carney, L. G. (1998). Hyperopia is predominantly axial in nature. *Current Eye Research*, *17*(4), 380–383. https://doi.org/10.1080/02713689808951218

sunrise-and-sunset.com. *Sonnenaufgang und Sonnenuntergang in Dortmund: September 2022* [Sunrise and sunset in Dortmund: September 2022]. https://www.sunrise-and-sunset.com/de/sun/deutschland/dortmund/2022/september

Swystun, A. G., & Davey, C. J. (2021). Exploring the effect of optometrist practice type on NHS funded sight test outcome. *Journal of Optometry*, *14*(1), 69–77. https://doi.org/10.1016/j.optom.2020.03.008

Tandon, P. S., Saelens, B. E., Zhou, C., Kerr, J., & Christakis, D. A. (2013). Indoor versus outdoor time in preschoolers at child care. *American Journal of Preventive Medicine*, *44*(1), 85–88. https://doi.org/10.1016/j.amepre.2012.09.052

Tanrıverdi, C., Tabakcı, B. N., Kılıç, A., & Mrochen, M. C. (2019, April 28-May 2). *Objective Measurement of Photopic Illuminance Rate in Daily Life of Progressive Myopic Children* [Poster presentation]. ARVO Annual Meeting, Vancouver, BC, Canada. https://www.vivior.com/files/download/arvo_poster_cafer_22.22.26.pdf/documents

Teberik, K., Eski, M. T., Kaya, M., & Ankarali, H. (2018). A Comparison of Three Different Photoscreeners in Children. *Journal of Pediatric Ophthalmology and Strabismus*, *55*(5), 306–311. https://doi.org/10.3928/01913913-20180405-03

Tedja, M. S., Haarman, A. E. G., Meester-Smoor, M. A., Kaprio, J., Mackey, D. A., Guggenheim, J. A., Hammond, C. J., Verhoeven, V. J. M., & Klaver, C. C. W. (2019). Imi - Myopia Genetics Report. *Investigative Ophthalmology & Visual Science*, *60*(3), M89-M105. https://doi.org/10.1167/iovs.18-25965

ten Velde, G., Lubrecht, J., van Loo, C., Hesselink, M., Reijnders, D., & Vreugdenhil, A. (2021). Physical activity behaviour and screen time in Dutch children during the COVID-19 pandemic: Pre-, during- and post-school closures. *Pediatric Obesity*, *16*(9), e12779. https://doi.org/10.1111/ijpo.12779

Thorn, F., Chen, J. [Jie], Li, C., Jiang, D., Chen, W., Lin, Y., Chang, X., Deng, R., & Chen, Y. [Yanyan] (2020). Refractive status and prevalence of myopia among Chinese primary school students. *Clinical & Experimental Optometry*, *103*(2), 177–183. https://doi.org/10.1111/cxo.12980

Tideman, J. W. L., Polling, J. R., Hofman, A., Jaddoe, V. W., Mackenbach, J. P., & Klaver, C. C. (2018). Environmental factors explain socioeconomic prevalence differences in myopia in 6-year-old children. *The British Journal of Ophthalmology*, *102*(2), 243–247. https://doi.org/10.1136/bjophthalmol-2017-310292

Time and Date AS. *Wetter-Rückblick für Dortmund, Nordrhein-Westfalen, Deutschland: September 2022* [Weather review for Dortmund, North Rhine-Westphalia, Germany: September 2022]. https://www.timeanddate.de/wetter/deutschland/dortmund/rueckblick?month=9&year=2022

Truckenbrod, C., Meigen, C., Brandt, M., Vogel, M., Sanz Diez, P., Wahl, S., Jurkutat, A., & Kiess, W. (2021). Longitudinal analysis of axial length growth in a German cohort of healthy children and adolescents. *Ophthalmic and Physiologival Optics*, *41*(3), 532–540. https://doi.org/10.1111/opo.12817

Ulaganathan, S., Read, S. A., Collins, M. J., & Vincent, S. J. (2017). Measurement Duration and Frequency Impact Objective Light Exposure Measures. *Optometry and Vision Science*, *94*(5), 588–597. https://doi.org/10.1097/OPX.0000000000001041

Ulaganathan, S., Read, S. A., Collins, M. J., & Vincent, S. J. (2019a). Daily axial length and choroidal thickness variations in young adults: Associations with light exposure and longitudinal axial length and choroid changes. *Experimental Eye Research*, *189*, 107850. https://doi.org/10.1016/j.exer.2019.107850

Ulaganathan, S., Read, S. A., Collins, M. J., & Vincent, S. J. (2019b). Influence of seasons upon personal light exposure and longitudinal axial length changes in young adults. *Acta Ophthalmologica*, *97*(2), e256-e265. https://doi.org/10.1111/aos.13904

Upadhyay, U. D., & Lipkovich, H. (2020). Using online technologies to improve diversity and inclusion in cognitive interviews with young people. *BMC Medical Research Methodology*, *20*(1), 159. https://doi.org/10.1186/s12874-020-01024-9

van Duijnhoven, J., Aarts, M. P. J., Aries, M. B. C., Böhmer, M. N., & Rosemann, A. L. P. (2017). Recommendations for measuring non-image-forming effects of light: A practical method to apply on cognitive impaired and unaffected participants. *Technology and Health Care: Official Journal of the European Society for Engineering and Medicine*, *25*(2), 171–186. https://doi.org/10.3233/THC-161258

van Gelder, M. M. H. J., Bretveld, R. W., & Roeleveld, N. (2010). Web-based questionnaires: The future in epidemiology? *American Journal of Epidemiology*, *172*(11), 1292–1298. https://doi.org/10.1093/aje/kwq291

Verkicharla, P. K., Ramamurthy, D., Nguyen, Q. D., Zhang, X., Pu, S.-H., Malhotra, R., Ostbye, T., Lamoureux, E. L., & Saw, S.-M. (2017). Development of the FitSight Fitness Tracker to Increase Time Outdoors to Prevent Myopia. *Translational Vision Science & Technology*, *6*(3), 20. https://doi.org/10.1167/tvst.6.3.20

Vivior AG. (n. d.). *Vivior Mark 3+: Technical Information.*

Wahl, M. D., Fishman, D., Block, S. S., Baldonado, K. N., Friedman, D. S., Repka, M. X., & Collins, M. E. (2021). A Comprehensive Review of State Vision Screening Mandates for Schoolchildren in the United States. *Optometry and Vision Science*, *98*(5), 490–499. https://doi.org/10.1097/OPX.0000000000001686

Wang, J. [Jianyong], Ying, G.-S., Fu, X., Zhang, R., Meng, J., Gu, F., & Li, J. (2020). Prevalence of myopia and vision impairment in school students in Eastern China. *BMC Ophthalmology*, *20*(1), 2. https://doi.org/10.1186/s12886-019-1281-0

Wang, J. [Jing], He, X.-G., & Xu, X. (2018). The measurement of time spent outdoors in child myopia research: A systematic review. *International Journal of Ophthalmology*, *11*(6), 1045–1052. https://doi.org/10.18240/ijo.2018.06.24

Wang, L., & Yu, J. (2023). Principles of photocatalysis. In *Interface Science and Technology. S-scheme Heterojunction Photocatalysts - Fundamentals and Applications* (Vol. 35, pp. 1–52). Elsevier. https://doi.org/10.1016/B978-0-443-18786-5.00002-0

Ware, J. (1813). IV. Observations relative to the near and distant sight of different persons. *Philosophical Transactions of the Royal Society of London*, *103*, 31–50. https://doi.org/10.1098/rstl.1813.0007

Watcharapalakorn, A., Poyomtip, T., & Tawonkasiwattanakun, P. (2022). Coronavirus disease 2019 outbreak and associated public health measures increase the progression of myopia among children and adolescents: Evidence synthesis. *Ophthalmic and Physiological Optics*, *42*(4), 744–752. https://doi.org/10.1111/opo.12976

We Are Social, DataReportal, & Meltwater. (2023a). *Distribution of Facebook useres worldwide as of January 2023, by age and gender*. https://www.statista.com/statistics/376128/facebook-global-user-age-distribution/

We Are Social, DataReportal, & Meltwater. (2023b). *Distribution of Instagram users worldwide as of January 2023, by age and gender*. https://www.statista.com/statistics/248769/age-distribution-of-worldwide-instagram-users/

Wen, L., Cao, Y., Cheng, Q., Li, X. [Xiaoning], Pan, L., Li, L., Zhu, H., Lan, W., & Yang, Z. (2020). Objectively measured near work, outdoor exposure and myopia in children. *The British Journal of Ophthalmology*, *104*(11), 1542–1547. https://doi.org/10.1136/bjophthalmol-2019-315258

Wen, L., Cao, Y., Huang, Y., Wu, Y., Li, X. [Xiang], Lan, W., & Yang, Z. (2017). Diverse visual behavior patterns in students in the same classroom. *Investigative Ophthalmology & Visual Science*, *58*(8), 2403. https://iovs.arvojournals.org/article.aspx?articleid=2640026

Wen, L., Cheng, Q., Cao, Y., Li, X. [Xiaoning], Pan, L., Li, L., Zhu, H., Mogran, I., Lan, W., & Yang, Z. (2021). The Clouclip, a wearable device for measuring near-work and outdoor time: Validation and comparison of objective measures with questionnaire estimates. *Acta Ophthalmologica*, *99*(7), e1222-e1235. https://doi.org/10.1111/aos.14785

Wen, L., Cheng, Q., Lan, W., Cao, Y., Li, X. [Xiaoning], Lu, Y. [Yiqiu], Lin, Z. [Zhenghua], Pan, L., Zhu, H., & Yang, Z. (2019). An Objective Comparison of Light Intensity and Near-Visual Tasks Between Rural and Urban School Children in China by a Wearable Device Clouclip. *Translational Vision Science & Technology*, *8*(6), 15. https://doi.org/10.1167/tvst.8.6.15

Wesemann, W. (2017). Analyse der Brillenstärken zeigt keine Zunahme der Myopie in Deutschland von 2000 bis 2015 [Analysis of spectacle lens prescriptions shows no increase of myopia in Germany from 2000 to 2015]. *Der Ophthalmologe: Zeitschrift der Deutschen Ophthalmologischen Gesellschaft*, *115*(5), 409–417. https://doi.org/10.1007/s00347-017-0601-0

Wesemann, W. (2018). Häufigkeit der Brillenträger in Deutschland: Deutliche Zunahme von 1952–2014 [Prevalence of spectacle wearers in Germany: Clear increase from 1952-2014]. *Der Ophthalmologe: Zeitschrift der Deutschen Ophthalmologischen Gesellschaft*, *115*(5), 421–423. https://doi.org/10.1007/s00347-018-0698-9

Wesemann, W. (2019). Veränderungen der Myopieprävalenz können aus Brillendaten abgeleitet werden [Changes in the prevalence of myopia can be derived from prescription data of spectacle lenses]. *Der Ophthalmologe: Zeitschrift der Deutschen Ophthalmologischen Gesellschaft*, *116*(7), 684–686. https://doi.org/10.1007/s00347-019-0916-0

Wetzel, E., Böhnke, J. R., & Brown, A. (2016). Response biases. In F. T. L. Leong, D. Bartram, F. M. Cheung, K. F. Geisinger, & D. Iliescu (Eds.), *The ITC International Handbook of Testing and Assessment* (1st ed.). Oxford University Press.

Wickham, H., Chang, W., Henry, L., Pedersen, T. L., Takahashi, K., Wilke, C., Woo, K., Yutani, H., Dunnington, D., & Posit PBC. (2023). *ggplot2: Create Elegant Data Visualisations Using the Grammar of Graphics* (Version 3.4.2) [Computer software]. https://cran.r-project.org/package=ggplot2

Williams, K. M., Bertelsen, G., Cumberland, P., Wolfram, C., Verhoeven, V. J. M., Anastasopoulos, E., Buitendijk, G. H. S., Cougnard-Grégoire, A., Creuzot-Garcher, C., Erke, M. G., Hogg, R., Höhn, R., Hysi, P., Khawaja, A. P., Korobelnik, J.-F., Ried, J., Vingerling, J. R., Bron, A., Dartigues, J.-F., . . . Hammond, C. J. (2015). Increasing Prevalence of Myopia in Europe and the Impact of

Education. *Ophthalmology*, *122*(7), 1489–1497. https://doi.org/10.1016/j.ophtha.2015.03.018

Williams, K. M., Verhoeven, V. J. M., Cumberland, P., Bertelsen, G., Wolfram, C., Buitendijk, G. H. S., Hofman, A., van Duijn, C. M., Vingerling, J. R., Kuijpers, R. W. A. M., Höhn, R., Mirshahi, A., Khawaja, A. P., Luben, R. N., Erke, M. G., Hanno, T. von, Mahroo, O., Hogg, R., Gieger, C., . . . Hammond, C. J. (2015). Prevalence of refractive error in Europe: The European Eye Epidemiology (E(3)) Consortium. *European Journal of Epidemiology*, *30*(4), 305–315. https://doi.org/10.1007/s10654-015-0010-0

Williams, R., Bakshi, S., Ostrin, E. J., & Ostrin, L. A. (2019). Continuous Objective Assessment of Near Work. *Scientific Reports*, *9*(1), 6901. https://doi.org/10.1038/s41598-019-43408-y

Wilson, S., Ctori, I., Shah, R., Suttle, C., & Conway, M. L. (2022). Systematic review and meta-analysis on the agreement of non-cycloplegic and cycloplegic refraction in children. *Ophthalmic and Physiological Optics*, *42*(6), 1276–1288. https://doi.org/10.1111/opo.13022

Wood, S. (2017). *Generalized Additive Models: An Introduction with R* (2nd ed.). Chapman & Hall/CRC.

Woods, A. T., Velasco, C., Levitan, C. A., Wan, X., & Spence, C. (2015). Conducting perception research over the internet: A tutorial review. *PeerJ*, *3.* https://doi.org/10.7717/peerj.1058

World Health Organization. (2016). *The Impact of Myopia and High Myopia: Report of the Joint World Health Organization - Brien Holden Vision Institute Global Scientific Meeting on Myopia*. https://myopiainstitute.org/wp-content/uploads/2020/10/Myopia_report_020517.pdf

Wu, P.-C. [Pei-Chang], Chen, C.-T., Chang, L.-C., Niu, Y.-Z., Chen, M.-L., Liao, L.-L., Rose, K., & Morgan, I. G. (2020). Increased Time Outdoors Is Followed by Reversal of the Long-Term Trend to Reduced Visual Acuity in Taiwan Primary School Students. *Ophthalmology*, *127*(11), 1462–1469. https://doi.org/10.1016/j.ophtha.2020.01.054

Wu, P.-C. [Pei-Chang], Chen, C.-T., Lin, K.-K., Sun, C.-C., Kuo, C.-N., Huang, H.-M., Poon, Y.-C., Yang, M.-L., Chen, C.-Y., Huang, J.-C., Wu, P.-C. [Pei-Chen], Yang, I.-H., Yu, H.-J., Fang, P.-C., Tsai, C.-L., Chiou, S.-T., & Yang, Y.-H. (2018). Myopia Prevention and Outdoor Light Intensity in a School-Based Cluster Randomized Trial. *Ophthalmology*, *125*(8), 1239–1250. https://doi.org/10.1016/j.ophtha.2017.12.011

Wu, P.-C. [Pei-Chang], Tsai, C.-L., Wu, H.-L., Yang, Y.-H., & Kuo, H.-K. (2013). Outdoor activity during class recess reduces myopia onset and progression in school children. *Ophthalmology*, *120*(5), 1080–1085. https://doi.org/10.1016/j.ophtha.2012.11.009

Xiang, Z.-Y., & Zou, H.-D. (2020). Recent Epidemiology Study Data of Myopia. *Journal of Ophthalmology*, *2020*, 4395278. https://doi.org/10.1155/2020/4395278

Xiong, S., Sankaridurg, P., Naduvilath, T., Zang, J., Zou, H., Zhu, J., Lv, M., He, X. [Xiangui], & Xu, X. (2017). Time spent in outdoor activities in relation to myopia prevention and control: A meta-analysis and systematic review. *Acta Ophthalmologica*, *95*(6), 551–566. https://doi.org/10.1111/aos.13403

Yang, L., Vass, C., Smith, L., Juan, A., & Waldhör, T. (2020). Thirty-five-year trend in the prevalence of refractive error in Austrian conscripts based on 1.5 million participants.

The British Journal of Ophthalmology, *104*(10), 1338–1344. https://doi.org/10.1136/bjophthalmol-2019-315024

Yang, M., Luensmann, D., Fonn, D., Woods, J., Jones, D., Gordon, K., & Jones, L. (2018). Myopia prevalence in Canadian school children: A pilot study. *Eye (London, England)*, *32*(6), 1042–1047. https://doi.org/10.1038/s41433-018-0015-5

Ye, B., Liu, K., Cao, S., Sankaridurg, P., Li, W., Luan, M., Zhang, B., Zhu, J., Zou, H., Xu, X., & He, X. [Xiangui] (2019). Discrimination of indoor versus outdoor environmental state with machine learning algorithms in myopia observational studies. *Journal of Translational Medicine*, *17*(1), 314. https://doi.org/10.1186/s12967-019-2057-2

Yotsukura, E., Torii, H., Ozawa, H., Hida, R. Y., Shiraishi, T., Corso Teixeira, I., Rautha, Y. V. B. L., Moraes do Nascimento, C. F., Mori, K., Uchino, M., Kurihara, T., Negishi, K., & Tsubota, K. (2020). Axial Length and Prevalence of Myopia among Schoolchildren in the Equatorial Region of Brazil. *Journal of Clinical Medicine*, *10*(1). https://doi.org/10.3390/jcm10010115

Zhang, X. J., Zhang, Y., Kam, K. W., Tang, F., Li, Y. [Yi], Ng, M. P. H., Young, A. L., Ip, P., Tham, C. C., Chen, L. J., Pang, C. P., & Yam, J. C. (2023). Prevalence of Myopia in Children Before, During, and After COVID-19 Restrictions in Hong Kong. *JAMA Network Open*, *6*(3), e234080. https://doi.org/10.1001/jamanetworkopen.2023.4080

Zhang, Z., & Wang, L. P. (2017). *Advanced statistics using R*. Granger, IN: ISDSA Press. https://advstats.psychstat.org

Ziemssen, F. (2018). Keine Zunahme der Myopie? [No increase in myopia?]. *Der Ophthalmologe: Zeitschrift der Deutschen Ophthalmologischen Gesellschaft*, *115*(5), 418–421. https://doi.org/10.1007/s00347-018-0697-x

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