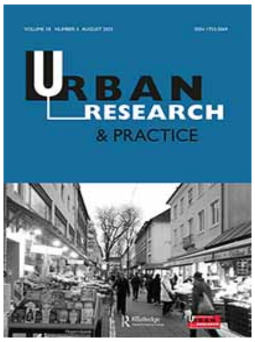


Urban Research & Practice

ISSN: 1753-5069 (Print) 1753-5077 (Online) Journal homepage: www.tandfonline.com/journals/rurp20

Associations between sense of place and the geometric shape complexity of corresponding self-reported spatial footprints from Lisbon, Portugal

René Westerholt & Albert Acedo

To cite this article: René Westerholt & Albert Acedo (2025) Associations between sense of place and the geometric shape complexity of corresponding self-reported spatial footprints from Lisbon, Portugal, Urban Research & Practice, 18:3, 415-467, DOI: 10.1080/17535069.2024.2422630

To link to this article: https://doi.org/10.1080/17535069.2024.2422630

URBAN RESEARCH & PRACTICE
2025, VOL. 18, NO. 3, 415–467
https://doi.org/10.1080/17535069.2024.2422630

Routledge
Taylor & Francis Group

Associations between sense of place and the geometric shape complexity of corresponding self-reported spatial footprints from Lisbon, Portugal

René Westerholt[a] and Albert Acedo[b]

[a]Department of Spatial Planning, TU Dortmund University, Dortmund, Germany; [b]NOVA Information Management School, Universidade Nova de Lisboa, Lisbon, Portugal

ABSTRACT
This article investigates how people translate the complex concept of sense of place into reductionist geospatial footprints. Utilising a map-supported survey conducted in Lisbon, statistical shape complexity measures, and logistic regression, we show that the number of mapped polygonal footprint vertices correlates with the sense-of-place dimensions of place identity and place attachment. Furthermore, we show that places to which people connect particularly close lead to more complex forms of shape complexity beyond the number of mapped points. Our findings contribute to the discourse on place-based information and to an improved understanding of the nexus between place and its geometric representation.

ARTICLE HISTORY
Received 3 April 2024
Accepted 23 October 2024

KEYWORDS
Sense of place; place; spatial footprint; shape complexity; platial information

1. Introduction

People do not live their lives in coordinates, but in meaningful places (Goodchild 2015).[1] Notions like home, workplace, favourite places, and nostalgic holiday experiences have in common that they carry a meaning and possibly an emotional attachment that can vary depending on the intensity and duration of our place engagement (Raymond, Kyttä, and Stedman 2017). The concept of place is an important one in both human geography and spatial planning, and has received increasing attention since at least the 1970s. Several schools of thought have emerged to conceptualise the construct of place: humanistic geography, which traditionally draws on an essentialist ontology (Seamon 2018; Tuan 2006) but has been complemented by a 'progressive' (non-essentialist) understanding (Lewicka et al. 2019; Massey 2005, 2008); critical approaches such as Marxist, feminist and postcolonial understandings, which draw on processual ontologies (Cresswell 2002; Dyck 2005; Harvey 1996); non-representational theories of place, which invoke performativity (Anderson 2016; Thrift 2008); and poststructural thinking including actor-network and assemblage theory, which build on part-whole relationships and emergence (Dovey 2020; Woods

CONTACT René Westerholt rene.westerholt@tu-dortmund.de

et al. 2021). This list is not exhaustive, but it shows that there exists a multitude of ways of conceptualising and understanding places and treating them analytically. All the approaches listed resist reductionism and are based on notions of wholeness (Cresswell 2015), that is, they consider place as an inseparable whole (Seamon 2018, 21) and require epistemological holism (Ianulardo and Stella 2022). In contrast, alternative approaches have become popular in more formal and quantitative considerations of place that fall within the realm of psychometric analysis (see Rust and Golombok 2014). Psychometric approaches abandon the property of wholeness and allow for reductionist, atomistic operationalisations that break place down into component parts. Properties based on wholeness are lost but formalisation becomes easier, and with it the application of statistical and other quantitative or formal methods. The present article borrows from both approaches by combining a psychometric analysis strategy with the humanistic construct of sense of place to investigate possible relationships between different dimensions of sense of place and geometric properties of corresponding spatial representations.

Sense of place describes a bond between people and their geographical surroundings (Seamon and Larsen 2020). This can be understood in two ways: as making sense of places (Seamon 2018) and as bonding in an emotional manner (Agnew 1987; Tuan 1977). Both interpretations play an important role in spatial planning. Urban design, for example, aims to create environments that people feel connected to and that make sense to them. Thus, urban design is partly about creating the conditions for people to develop a sense of place that can eventually generate feelings of authenticity, character, identity, community, and joy (Ellery and Ellery 2019; Hårsman Wahlström, Kourtit, and Nijkamp 2020; Jive´n and Larkham 2003; Salah Ouf 2001). There is also much literature that demonstrates the positive effects of a strong sense of place on public health. With reference to so-called therapeutic landscapes (see Williams 2017), a positive sense of place has been shown to contribute to mental well-being in a number of ways (Basu, Hashimoto, and Dasgupta 2020; Bell et al. 2018; DeMiglio and Williams 2008). For example, Tomalin, Sadgrove, and Summers (2019) show how places of worship support the well-being of Black, Asian, and other minority ethnic groups in Britain, primarily by offering support networks; Marques et al. (2020) show how the health of New Zealand's Māori population suffers from the colonially induced and continually maintained design and structuring of places that is culturally inappropriate for them; and Doughty, Hu, and Smit (2023) show how the COVID-19 pandemic increased people's attachment to local greenspaces and nearby nature reserves, which effectively turned into place-based health resources. In contrast, the lack of positive place attachment can lead to an increase in body weight (Santana and Nogueira 2008), an increase in drug addiction (Proudfoot 2019), among other adverse effects. Other relevant aspects of the importance of sense of place for planning include the role that the presence of urban amenities plays in place identity and place attachment (Westerholt, Acedo, and Naranjo-Zolotov 2022), ensuring the sustainability of intangible cultural heritage (Tan et al. 2018), and place stewardship (Chapin and Knapp 2015). Many more intersections between spatial planning and sense of place could be pointed out, but the brief discussion above should offer an impression of how sense of place feeds into planning research and practice. Taking account of sense of place in planning often includes not only the results of surveys or interviews, but also geometric sketches of the map locations associated with sense of place (e.g. by residents), as is evident from the literature on public participation. Understanding the process by which people translate their sense of place into polygons (one type of geometric representation besides points and lines) is therefore important for a comprehensive understanding of geometric representations of place.

The aim of this study is to understand better the process of translating the complex construct of experienced, lived place into reductionist spatial footprints that delineate geometrically the associated territories on a map. The relationship between space and place remains contested and is subject to specific place conceptualisations (for a discussion, see Kabachnik 2012). However, we argue that space, understood here in a geometric manner,[2] plays a certain role in place and that the territory attached to the latter can often be pinpointed on a map through a reduction step. Respective footprints were collected by us through a web-based, map-supported survey comprising the self-reported footprints of 230 respondents from Lisbon, Portugal. Our employed mapping technique is sketch mapping, which is defined as 'participants sketching onto aerial images, base maps, or tracing paper, unlike the free-form blank paper drawings of mental mapping [and yielding] representations of individual and group spatial experiences' (Boschmann and Cubbon 2014, 239). The recorded dimensions of sense of place – place identity, place attachment, and place dependence – are not lost in the reduction step, but remain in the form of individual variables (reflecting the psychometric approach) collected through a companion survey.

Our hypothesis is that the geometric parameters of the self-reported footprints are correlated with at least some of the more detailed operationalisations of the aforementioned sense-of-place components. The underlying assumption is that people[3] drawing respective polygons more carefully and in more complex ways also report stronger or weaker sense of place scores. Following Jeff Malpas (2018, 48 *ff.*), who states that meaningful engagement in (humanistic) place-making always-already requires a certain degree of grasping geometric space and self-positioning within it, we assume that people have a rough geometric idea of the spatial location, contours, and shape of their meaningful places. When we ask them to convert these mental images into footprints, we assume that people approximate those contours in the form of polygons. We apply statistical measures of shape complexity and correlate the results with our collected sense of place variables. The hypothesis we are testing, then, is that people incorporate a stronger, positive (or negative) sense of place (or individual dimensions thereof) into their translation process between the mental image and the geometric mappings of the corresponding locations. In this way, subjects could, for example (and presumably subconsciously), express their attitudes towards their meaningful places, as well as their possibly higher degree of familiarity with the associated territories based on their lived experience with them. Utilising the sketched approach and rationale, this article presents links between geometric properties of geometric place representations and the strength of certain sense of place dimensions.

The remainder of this article begins with a literature review in Section 2, which presents work on the spatial mapping of place. Drawing on this overview, Section 3 first elaborates in more detail on the theoretical basis of our approach, already sketched above, before presenting the concrete methods used. This is followed by a presentation of the results in Section 4 before we discuss them and give final conclusions and comments for future research in Section 5. We hope that our results will inform planning research and practice in a broad manner.

2. State of the art

Assessing spatial footprints of place via sketch mapping[4] is an established practice in human geography, planning, environmental psychology, and related fields. The two most common approaches are punctiform and polygonal sketch mapping, along which the subsequent paragraphs summarise the current state of the art. We thereby deliberately take into account different types of place concepts, including those beyond humanistic geography, as, we argue, the underlying object of investigation is comparable across different schools of thought in that they inherently link space and place instead of considering them dichotomous.[5] David Seamon, for example, in his humanistic notion of 'place ballet', considers habitual routines as a means of transforming space into place (Seamon 2018, 15). Similarly, but from a post-structuralist perspective, Michel de Certeau describes place as practised space (de Certeau 1984).[6] What is consistent between different place discourses is that they recognise a dualism between space and place – as we presuppose in this work through our footprints – which is why we do not limit our review to strictly humanistic works. The types of mapping[7] presented below deal with self-reported place footprints as we do in the analysis that follows. Other approaches in which researchers construct geometries post hoc from texts or interviews (e.g. Adams and McKenzie 2012; Cooper and Gregory 2011; Hobel, Fogliaroni, and Frank 2016; C. B. Jones et al. 2008; Kim, Vasardani, and Winter 2016; Steiner et al. 2023; Wartmann, Acheson, and Purves 2018; Woodcock, Wollan, and Dovey 2015), deep mapping (a technique from the humanities that allows obtaining comprehensive snapshots of places; e.g. Alavez 2022; de Nardi 2014; Savić 2017), and visualising spatial footprints of place (e.g. Bleisch and Hollenstein 2018; Dolma 2022; Glebova 2022; Gröbe and Burghardt 2018; Iosifescu Enescu et al. 2020; Westerholt et al. 2018), among others, are not discussed as they differ too much from our own research presented in this article. We also do not address the literature on predictors and contextual parameters of place attachment, place identity, and place dependence. Some control variables are included in our modelling (see Section 3.3), but the focus of our work is on understanding geometrically the spatial footprints of place. We therefore refer readers interested in the constituents and predictors of the aforementioned dimensions of sense of place to relevant reviews and overviews (e.g. Alrobaee and Al-Kinani 2019; Azmi, Ahmad, and Ali 2014; Lengen and Kistemann 2012; Lewicka 2011; Nelson, Ahn, and Corley 2020; Peng, Strijker, and Wu 2020; Qazimi 2014; Shamai and Ilatov 2005).

One way to collect self-reported place footprints is to collect point data. In a similar approach to ours, Hasanzadeh, Laatikainen, and Kyttä (2018) used a web-mapping-based survey to collect personally relevant places of daily life in Helsinki, Finland (an application for which they also introduce a privacy strategy, see Hasanzadeh et al. 2020). The collected points were then combined in activity space models (which differs from the research objective in this paper), and the results show that the polygon sizes yielded correlate with income and (via elongation) with residence location in a suburb.

These results are interesting, but could be affected by underlying urban characteristics in the Scandinavian context, such as people with higher incomes often living in suburban communities (Hassler and Ceccato 2021) but finding fewer opportunities nearby (Næss 2016). Similarly, Hawthorne et al. (2022) recently mapped points of place attachment, which they combined into areal representations using variants of kernel density estimation. There are a number of studies that take similar approaches (e.g. Gagnon and Desbiens 2018; Jeannotte 2015; L. Jones et al. 2020; Kosacz et al. 2022; Maddrell 2016; Müller, Backhaus, and Buchecker 2020; Spenger, Kordel, and Weidinger 2023; Twaroch et al. 2019; Zelianskaia et al. 2020). Although these are related to our work, they are not directly comparable, as the respondents themselves do not record their own polygonal features. Another point-based form of place mapping is the extraction of place information from publicly accessible user-generated, bottom-up web content. Bahrehdar, Koblet, and Purves (2019) have systematically reviewed corresponding approaches and categorise them into images, microblogs (mostly Twitter/X), check-ins, and unstructured texts. They conclude that in most cases spatial place footprints are not the focus as such, but serve to answer other, domain-specific empirical questions. The most limited such approach in terms of spatial footprints is check-in data. Users of such services can only check-in at a finite set of predefined sites (e.g. Adelfio et al. 2020; Jang, Kim, and Schifanella 2019; McKenzie and Adams 2017; Wu et al. 2019). Apart from check-in behaviours, the resulting points mainly reflect the spatial patterns of the underlying distribution of venues, making them less interesting footprints regarding sense of place. More flexible in terms of spatial footprint patterns is the analysis of data from geolocated microblogs, which have been shown to be correlated to a reasonable extent with socioeconomic and demographic characteristics (e.g. Ballatore and De Sabbata 2018, 2020; Steiger et al. 2015). Yet, the results of such studies also show that the spatial patterns in those points follow largely, though with local variations, the geography and demographics of the underlying platforms. For the purposes of this paper, the spatial footprints of places derived from user-generated web content are only partially comparable to our results, even though the point geometries are self-reported. This also applies to studies in which researchers combine individual points into grids or polygons reflecting colloquial or vague geographies (e.g. M. Chen, Arribas-Bel, and Singleton 2020; J. Chen and Shaw 2016; Clasper 2018; Heikinheimo et al. 2018; Hollenstein and Purves 2010; Jenkins et al. 2016; Li and Goodchild 2012; Liu et al. 2020; Lopez, Postma, and Bosco 2020; Poorthuis 2018; Schlieder and Matyas 2009; Twaroch et al. 2019), as such polygons are not reported by the users but constructed by the researchers retrospectively.

The second type of data is self-reported polygonal footprints of place and related notions. One relevant line of research undertaken from a spatial cognition point of view is the one conducted by Dan Montello, though his notion of 'vague cognitive region' seems closer to the geographical concept of region than place. One study conducted in Santa Barbara, CA (Montello et al. 2003) and employing a passers-by survey collected polygons reflecting generally people's spatial referents of 'downtown' including 50% and 100% certainty assessments. The general polygons drawn are, on average but with some variation, close to the 50% ones, indicating that people tend to be generous in their spatial judgements when answering geometric place enquiries. They further found that ca 2/3 exclusively drew convex polygons while only 1/5 of respondents exclusively drew concave ones. Montello, Friedman, and

Phillips (2014) extended a similar task to state level to delineate Northern and Southern California and Alberta. They used a cell-based approach revealing a broad band of non-uniform collective vagueness especially across California. This shows that the spatial footprints of cognitive regions can be spatially heterogeneous. In a further study, Phillips and Montello (2017) add to these findings the perspective of social neighbourhood ties, confirming that spatial representations of cognitive regions do often coincide with certain census characteristics, at least in Santa Barbara. The study most closely related to ours is concerned with mapping sense of place in Koreatown, Los Angeles (Bae and Montello 2018). While the responses show strong agreement regarding mapping, the accompanying open-ended survey provides evidence that aesthetics, social environment and utilitarian aspects have an influence, although these different aspects are not distinctly differentiated. Another relevant research stream is that of Angela Schwering and collaborators (Manivannan, Krukar, and Schwering 2022; Schwering et al. 2014, 2022; Wang and Schwering 2009, 2015; Wang, Mülligann, and Schwering 2011). The sketch maps considered in their research are more detailed than those used here, as they do not just focus on sketching vague boundaries. However, their research focuses on the translation process between the mental image of a region and its metric representation, which is part of what our respondents also do, albeit for a different reason. An important finding for us is that the road network seems to be an essential element in this process. Since we provide our participants with topographic base maps (see Section 3), we can expect a certain geometric bias towards higher geometric accuracy in our work, as the participants are confronted with a geometrically accurate road layout. This assumption is supported by another study of those listed above (see Wang and Schwering 2015) confirming a number of invariant characteristics of sketch maps (assessed from respondents with recurrent place interactions, like in our case), among which the road network plays a prominent role. There are a number of results from other researchers and from different contexts that largely confirm the above findings and complement them with further details and minor aspects (see Aram et al. 2019; Baker, Cantillon, and Evans 2023; Cerveny, Biedenweg, and McLain 2017; Costa and Bonetti 2018; Curiel and Radvansky 2004; G. A. Davis and Hyun 2005; Donnelly, Gamsu, and Whewall 2020; Gardony, Taylor, and Brunyé 2016; Gieseking 2013; Graves and Poraj-Wilczynska 2009; Hátlová and Hanus 2020; Lopez and Bosco 2022; Mohsenin 2011; Nanda and Khare 2018; Pánek, Glass, and Marek 2020; Potter 2015; Povilaitienė 2021; Powell 2008; Soini 2001; Wang and Worboys 2017; Zare Zardiny and Hakimpour 2021; Zhang, Tang, and Sheng 2024).

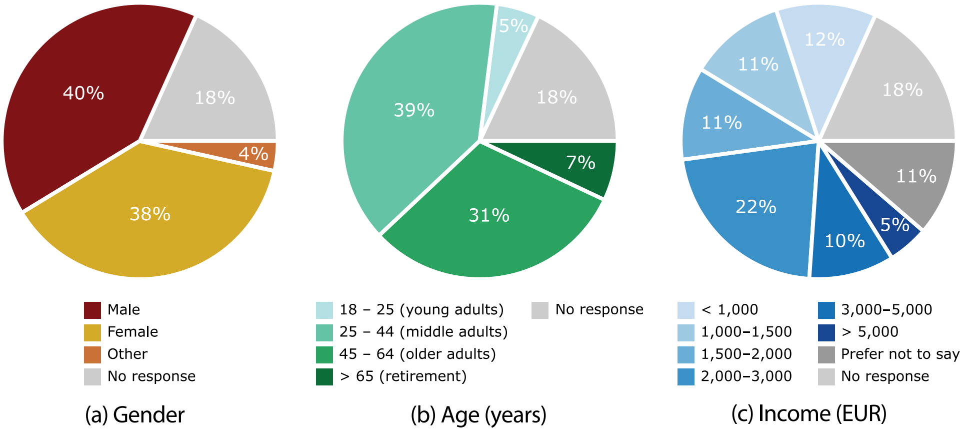
There is only limited research in which researchers link geometric properties of self-reported, sketch-mapped spatial footprints to explicit operationalisations of sense of place. Many of the above findings are therefore related to our research, but often refer to regions rather than places, or even to mixed forms without clear distinction. Montello et al. (2003), 188) state that '[in] practice, geographic regions are more likely to be identified by their limits than by enumerating their contents.' We argue that this statement is often more appropriate in reverse for the humanistic notion of place rather than regions, as people likely find it easier to enumerate the contents of what constitutes their 'home' (or other, sometimes possibly unnameable places) than to think about its boundaries. One consequence of this is that the probabilistic character of corresponding footprints (of which there may be many candidates) may be more pronounced compared to those of regions. With this in mind, our following research complements the above findings by: (i) extending them towards a deeper engagement with the spatial referents of the humanistic notion of sense of place; (ii) focusing on meaningful places that do not necessarily correspond to so-called points of interest (even though some places identified in our study may correspond to places of interest, such as popular parks); and (iii) linking these spatial representations to the results of an established quantitative operationalisation of three sense of place domains adopted from Jorgensen and Stedman (2001).

3. Methodology

Our methodology comprises three components. As a first step, we conducted a web-based and map-supported survey to collect data on sense of place including spatial footprints for the city of Lisbon. This survey is reported in Section 3.1. The second component involves quantifying the shape complexity of the collected geometric footprints. Section 3.2 introduces measures that we use to operationalise this property. The following Section 3.3 puts forward our employed regression modelling, which relates the geometric complexity scores with the sense of place responses.

3.1. *Map-supported online survey*

We used a map-based online survey to collect the data for this article. A link was emailed through Lisbon City Council to potential participants who had previously taken part in at least one of the council's public participation initiatives (which is why the council had their email addresses in their database). The full text of the invitation email in Portuguese and in English translation can be found in Appendix A. In total, 230 people with a minimum age of 18 years participated in the survey. The sample we collected in this way is reasonably representative of Lisbon's demographics and socio-economic profile (c.f. Pordata 2021a, 2021b). Figure 1 provides an overview of some key personal characteristics of our respondents. As we recruited all respondents through Lisbon City Council, we were able to ensure that every participant was a resident of the city at the time of the survey. To incentivise participation and recognise participants' efforts, we rewarded the



(a) Gender (b) Age (years) (c) Income (EUR)

Figure 1. Overview of the demographic and socioeconomic respondent characteristics ($n = 230$). The option 'prefer not to say' was only offered for the income variable, not for other respondent characteristics.

10th, 50th, 100th, and 200th participants with vouchers worth EUR 50 each. No personal data was collected that could lead to the identification of the participants. Furthermore, the participants were informed about the objectives of the data collection. On the data collection portal, respondents were then asked to indicate the places that are ‘significant’ to them (using this wording), followed by examples such as ‘identify most with’, ‘and/or feel connected to (e.g. I love this place)’ and ‘and/or depend on it (e.g. it is the most appropriate place to do the things I enjoy most)’. The way we introduced place therefore centred on the idea of ‘important to you’ (in the broadest sense).

The survey design operationalises the conceptualisation of sense of place introduced by Jorgensen and Stedman (2001), which has been widely used in environmental psychology and is an established conceptualisation. The model divides sense of place into three sub-components, namely place dependence (the added value of opportunities offered by places for meaningful experiences; referred to as PD1–PD3 in the remainder), place attachment (the emotional relatedness to a place; PA1–PA3), and place identity (the adoption of a place as part of the self; PI1–PI3). The survey to operationalise these three components consists of two parts: geometric sketch mapping and an assessment of statements about the three individual sense of place components. Participants were first asked to draw a series of polygons on a base map representing the places that respondents consider personally important. We have instructed our participants to use a desktop computer or laptop for completing the survey (see the invitation email in Appendix A). Most respondents will thus have used either a mouse or trackpad for their footprint mapping. A topographic OpenStreetMap background map using the standard OSM Carto rendering style was offered for this mapping, but no other technical aids or constraints. In a next step, respondents were presented with a series of statements for each polygon drawn. There are three statements per dimension of sense of place, which are listed in Table 1. Here we deviate slightly from the approach proposed by Jorgensen and Stedman (2001). Their breakdown of place components consists of four statements each. However, some of the proposed statements (namely IDENTITY2, DEPEND3, DEPEND4 in Jorgensen and Stedman (2001)) are phrased in a negating way and could have been perceived as contradicting with most of the other

Table 1. The queried statements used to operationalise the sense of place dimensions of place attachment, place identity, and place dependence. The statements are modified versions of those presented in Jorgensen and Stedman (2001).

Domain	Variable	Label	Statement
Place attachment	PA1	Easing	I feel relaxed when I’m in this area.
	PA2	Joy	I feel happiest when I’m in this area.
	PA3	Preference	This area is my favourite place to be.
Place identity	PI1	Personification	Everything about this area is a reflection of me.
	PI2	Oneself	I feel that I can really be myself in this area.
	PI3	Materialisation	This area reflects the type of person I am.
Place dependence	PD1	Suitability	This area is the best place for doing the things that I enjoy most.
	PD2	Uniqueness	For doing the things I enjoy most, no other place can compare to this area.
	PD3	Affordance	This area is a good place to do the things I like to do most.

The statements above have been translated and were presented to the Lisbon-based participants in Portuguese. The identifiers PA, PI, and PD (each numbered from 1 to 3) are used as variable names in Section 4.2. Please note that the labels in the third column are brief summaries for use in this article. They were not presented to the respondents in the survey.

statements. As respondents completed the surveys alone at home and without potential support from the researchers, we have omitted these possibly confusing statements. We have replaced DEPEND3 and 4 with a weaker alternative statement ('a good place to') to PD1, as the latter is quite strong ('the best place for'). In addition, the statement ATTACH4 was omitted as it focuses too much on the concept of 'home', which is the case under investigation in Jorgensen and Stedman (2001).

All statements were rated as 5-point Likert items ranging from 1 (strongly disagree) to 5 (strongly agree). Figure 2 shows the response distributions across all items. These generally tend towards agreement, which was to be expected as we asked respondents about places that are meaningful to them. The meaningfulness is thus reflected in the operationalisations. Alongside the place components, assessments of the sociability (how interactive, welcoming, neighbourly a place is), accessibility (how easy it is to reach a place), aesthetic qualities (the comfort and visual quality of a place to make one stay), and usability (utilitarian aspects of a place) of the mapped places were also collected and the corresponding statements are found in Appendix B. These characteristics have been identified as common factors for successful, positively received (public) places (Cilliers and Timmermans 2014). Furthermore, Bae and Montello (2018) found that these characteristics (e.g. visible barriers, ethnicity, language spoken) influence the way people map places. We therefore collect the corresponding subjective assessments of our respondents using Likert items to later use them as control variables for the reasons outlined above. The item distributions of these additional variables are also provided in Figure 2.

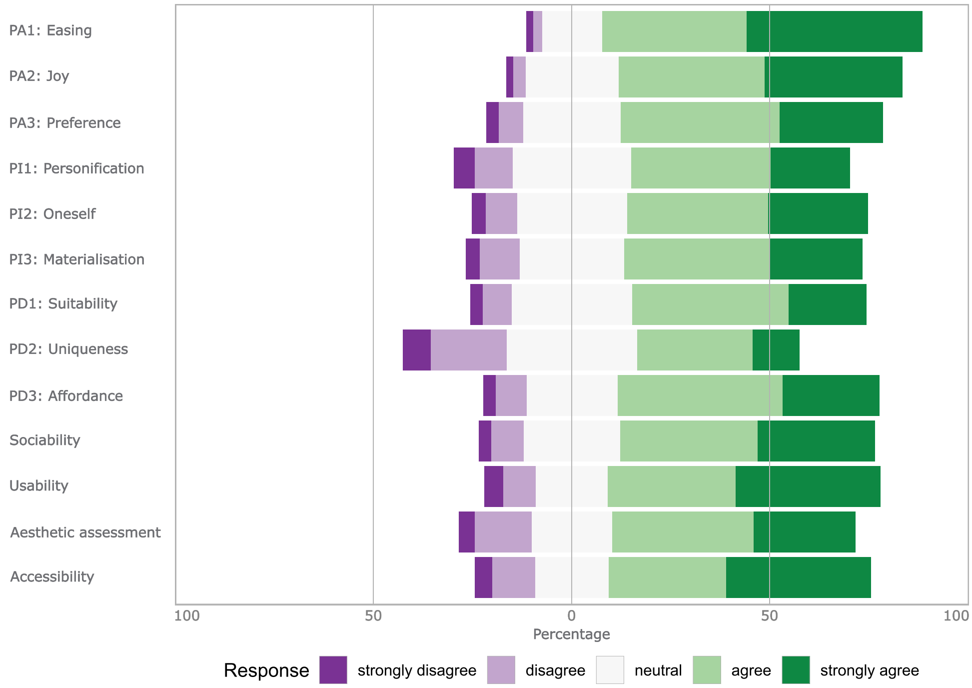


Figure 2. Distribution of the Likert item responses for the sense-of-place and the contextualising variables ($n = 230$).

Only after mapping several places and collecting respective survey responses did we ask respondents to identify one of the polygons they drew as the most important. The reason for this is that we wanted to avoid the risk of bias, as asking for the most important place at the beginning could have led to some participants drawing particularly carefully or could have influenced the evaluation of the statements. Another reason why we narrow down the total set of polygons to the most important ones is to make it easier to compare the polygons with each other. Otherwise, we might have ended up comparing someone's most important place with someone else's second or third most important place. In the manner executed, we have assembled a dataset comprising geometric footprints and corresponding ratings of statements to operationalise the outlined sense of place dimensions.

3.2. *Geometric complexity measures*

Different ways exist to characterise the complexity of a shape, for example, using methods from cartography or computer vision (e.g. Fairbairn 2006; Pászto, Brychtová, and Marek 2015; Zhu 2023). However, since we are not dealing with abstract shapes but with geometries representing personal reflections of the ways people think about places, the chosen measures should be consistent with relevant empirical evidence. Our methodology therefore builds on insights from the psychology of vision and we draw an analogy between the complex visual task of recognising contours in highly noisy images and the mental geospatial image that someone creates of a meaningful place against the background of a complex array of experienced geographic environments.

The way we measure shape complexity is inspired by the work conducted in psychology of vision and in particular the findings of Wilder, Feldman, and Singh (2016). In their article, the authors explore appropriate statistical measures of shape complexity to explain how this property is involved in our human ability to detect contours in noisy images. Sense of place goes beyond vision and encompasses a range of senses (among other, non-sensory aspects). Nevertheless, the spatial footprints we are dealing with in this article are visualisable representations of someone's idea of the territory associated with a place, and so we can think of the task at hand as resembling an inverse scenario to the work of Wilder, Feldman, and Singh (2016). The main reasons why we draw this analogy are the following: (i) due to the holistic character of places, we assume that respondents already have a rough idea of the whole area in mind before drawing a polygon (local approaches would also be possible, but there is ample evidence to support global precedence, see Miller 1981; Navon 1977; Rezvani, Katanforoush, and Pouretemad 2020); (ii) like the shapes dealt with by Wilder, Feldman, and Singh (2016) the collected footprints of sense of place always have a closed contour (though we also consider open contours when looking at polygonal skeletons, see below); (iii) we assume that statistical features of complexity are more related to geometric representations of sense of place than would be simpler features such as counting numbers of points or line segments, as the former reflects the stochastic nature attached to people's decisions for how to sketch a footprint. The latter assumption corresponds to a subset of the hypothesis we ultimately want to test in this paper and states that the effort and accuracy someone puts into drawing has something to do with the familiarity, subjective importance of, and affection towards the place in question. In addition, identifying contours involves integrating different pixel *candidates* into contours, and we argue that this, by analogy, is similar in nature for places that rarely possess only one clear geometric boundary in terms of their territory but offer a range of footprint candidates that sit in someone's mental representation instead. The analogy we draw is thus consistent with existing place research (e.g. Davies 2020; Winter and Freksa 2012) and the traditional challenge of drawing boundaries for geographical features, which are often (and not only for places) indeterminate and thus stochastic rather than deterministic in nature when represented (Smith 2019; Yang and Hillier 2007).

We employ a combination of a summary measure of overall shape complexity and of a measure of smoothness deviation (or 'spikiness') along the contour. Following Wilder, Feldman, and Singh (2016), our complexity assessment builds on a skeleton approach. Skeletons are based on medial axis representation and capture the general shape of polygons (see Aichholzer et al. 1995). We assume that people graphically imagine the territories assigned to their important places when they look at the map, which seems to happen via skeletons calculated by our visual system, as supported by psychological evidence (Ayzenberg et al. 2019; Lowet, Firestone, and Scholl 2018; Sun and Firestone 2021). We calculate both the skeletons and their associated medial axes using the open source SQL-based GIS package PostGIS (version 3.0).[8] To also account for the unevenness along the contours of the footprints, we further evaluate contour complexity in terms of turning angles. In both cases, we work with statistical characterisations of complexity inspired by the information-theoretic description length as introduced by Shannon (1948). The measures are given as

$$\mathrm{DLC}_i = -\sum_{j=1}^{m_i} \ln \frac{e^{\kappa_1 \cos\left(\alpha_{i,j}-\mu_1\right)}}{2\pi \mathrm{I}_0(\kappa_1)}, \tag{1a}$$

$$\mathrm{DLS}_i = \lambda - \ln\left(\frac{\lambda^{s_i}}{s_i!}\right) - \sum_{j=1}^{q_i} \ln \frac{e^{\kappa_2 \cos\left(\beta_{i,j}-\mu_2\right)}}{2\pi \mathrm{I}_0(\kappa_2)}, \tag{1b}$$

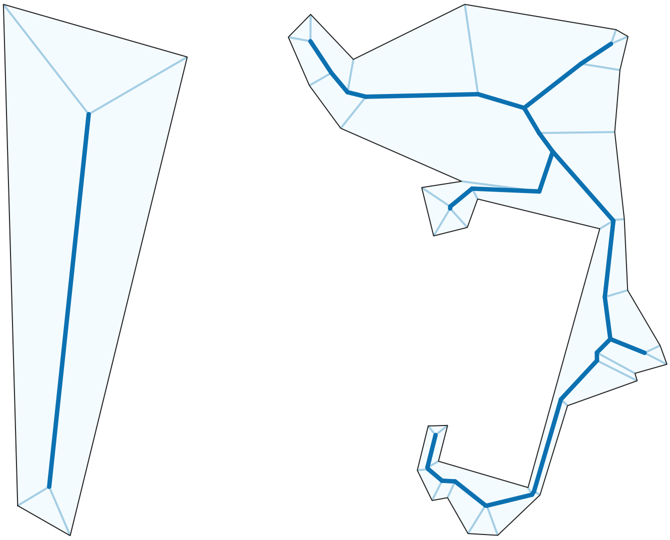
where i denotes the i-th of n footprints, $\alpha_{i,j}, \beta_{i,j}$ are m_i and q_i turning angles measured in radians, κ_1, κ_2 and μ_1, μ_2 denote the scaling and mean parameters of von Mises distributions and λ and s_i denote the mean parameter and i-th count of sprouts emanating from the respective medial axis and as used with a Poisson distribution. $\mathrm{I}_0(\cdot)$ is the modified Bessel function of order 0 (here a mere scaling constant). It is important to note that the turning angles $\alpha_{i,j}$ and $\beta_{i,j}$ are not the immediate turning angles between consecutive line segments. Shape complexity is measured here in terms of resemblance of smooth contours and, therefore, the angles are measured between a turning segment and the tangent to the respective turning point. Since tangents are only defined for differentiable functions (which edgy polygons are not), we need to approximate reasonable tangents from hypothesised smooth contours. The way respective tangents are approximated in this paper is outlined in Appendix C. The reason for assuming a null hypothesis based on smooth contours is that in our data acquisition the polygon points are set one after the other by repeated clicking. A more detailed drawing in this way therefore increases the edginess. This null hypothesis would have to be reversed if the data had been obtained from hand-drawing exercises.

Equation (1a) introduces the measure DLC_i that summarises the segment complexities of the footprint contours. The term in the summation represents the logarithm of the density of a von Mises distribution, for which the psychological literature provides strong indications that it is inherent in our visual stochastic system for recognising closed contours. The von Mises distribution can roughly be understood as the periodic counterpart of the normal distribution (Best and Fisher 1979). Since the contour is closed and we must therefore assume a bias of the angles in a certain direction, we work with a mean of $\mu_1 = 2\pi/m_i$, where m_i is the number of tangential angles contained in the sequence along the contour. The parameter κ_1 is not a direct dispersion but a precision parameter (like $1/\sigma^2$, for a normal distribution) and is therefore set to $4/\pi$ (assuming that the turns are on average half a perpendicular). In this way we can quantify how 'unpolished' or 'rough' the contour line is. Following the outlined reasoning, DLC_i yields high scores for abrupt, marked turning angles that would not be expected with high probability under the smooth contour null model. In contrast, a series of moderate turning angles with high von Mises-derived probabilities (yielding small DLC_i scores) would be closer to the reference of a smooth contour.

The measure DLS_i from equation (1b) reflects the complexity of a footprint's overall basic shape in terms of a skeleton. The statistical model allowing us to evaluate the probability of a given skeleton comprises two types of probabilities the underlying processes of which are assumed to be independent, and so the individual probabilities have been multiplied. One type of probability that goes into equation (1b) describes the angles of the medial axis of the skeleton. This is similar to the approach for DLC_i, but we are now dealing with an open contour. So we again use a von Mises distribution but with $\mu_2 = 0$, assuming a straight-line continuation in expectation. The precision parameter κ_2 is set to $4/\pi$, again assuming that the turns are half a perpendicular on average. The second type of probability involved in equation 2 is a Poisson density with $\lambda = 4$. This density models the number of sprouts s_i emanating from the medial axis of a footprint i. The chosen parametrisation gives the highest probability to the count of four (which is expected for simple rectangular shapes; see Figure 3(a)), thus favouring simple shapes with few sprouts. High numbers of sprouts that are indicative of more complex geometric shapes would yield lower probabilities, respectively. Overall, we assume that this model is appropriately sophisticated for reflecting the complexity of the footprint skeletons, yet reasonably manageable. Figure 3 illustrates examples of both complex and simple skeletons and contours.

3.3. *Logit regression modelling*

The modelling step serves to identify potential associations between the shape complexity scores (Section 3.2) and the Likert items operationalising sense of place (Section 3.1). Regression modelling could be approached from two directions: treating either the complexity scores or the Likert items as dependent variables. The histograms of both complexity scores (Figure 4) are right-skewed and visually resemble gamma distributions, which would suggest using either lognormal or gamma generalised linear models. However, both model types assume a constant coefficient of variation (Das and Park

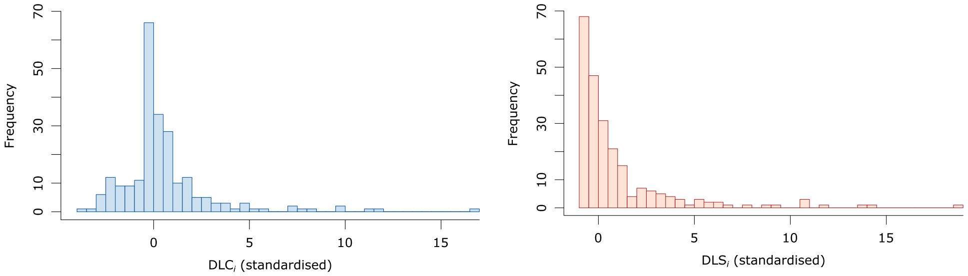


(a) Simple (b) Complex

Figure 3. Examples of simple and complex skeletons (dark blue centre lines; the corresponding sprouts are depicted as light blue lines) and contour lines (the black polygon boundaries). The DLS and DLC scores for the illustrative features shown are 1.63 and 11.66 for (a), and 75.73 and 42.05 for (b).

2012; Wiens 1999), which cannot be confirmed according to the asymptotic test for equality of the coefficient of variation (Feltz and Miller 1996) applied to both scores stratified into their quantiles and 12.5 % percentile ranges (to obtain results for broader and narrower substrata). This prohibits the use of lognormal and gamma models and would suggest the use of less convenient non-parametric models instead. The alternative approach – and the one that we opt for – is to consider the sense-of-place operationalisations as dependent variables. One possibility for this is to regard the response variables as ordinal, which suggests the use of ordinal proportional-odds logit regression. However, although many conditions are met, comparing parameter estimates for individual categories shows that the regression coefficients obtained may not be stable across all Likert categories. To deal with the latter issue, a baseline-category logit regression seems useful. This estimates the parameters for all categories separately and in relation to a reference category (here: the neutral third category). Yet, this approach leads to less reliable estimates due to subsetting and thus limited sample sizes per category. Since both approaches have their advantages and limitations, we perform both and interpret them in tandem.

Ordinal proportional-odds logit regression is suitable for modelling multinomial variables Y whose results can fall into J ordered categories. Let γ_j be cutpoint coefficients[9] for $j = 1, \ldots, J-1$ categories[10] and $\eta_1, \ldots, \eta_P$ be the regression coefficients for $p = 1, \ldots, P$ regressors X. The regression model used is given as (Grilli and Rampichini 2014)



(a) Contour complexity

(b) Skeleton complexity

Figure 4. Histograms of the two types of assessed statistical shape complexity scores. Both histograms show values centred on their respective sample medians and scaled according to their median absolute deviations.

$$\log\left(\frac{\mathrm{P}\,(Y \le j)}{\mathrm{P}\,(Y > j)}\right) = \gamma_j - \eta^{\mathrm{T}} X. \tag{2}$$

Note that only the cutpoint coefficients γ_j are bound to categories j. This reflects the so-called proportional odds assumption, which means that all coefficients except of those for the cutpoints are considered uniform across the categories of Y. The model predicts logarithmic expectations, which implies that the model coefficients are on the log scale, making it difficult to interpret the results. We therefore report the exp-transformed coefficients alongside the raw estimates in Section 4.2. In addition to the two shape complexity scores (interval-scaled real variables; see below for how we further post-processed the complexity scores), we use the control variables introduced in Section 3.1 to account for the respondents' perceptions of how sociable, accessible, aesthetically pleasing, and usable the places in question are.

Baseline-category logit regression ignores order in categories but offers category-wise coefficient estimates. The model is suitable for multinomial variables Y whose results can fall into $j = 1, \ldots, J$ categories. Let $\beta_{1j}, \ldots, \beta_{Pj}$ be the regression coefficients for P independent variables tied to categories j. The regression model used is given as (Agresti 2012, 293 *f.*)

$$\log\left(\frac{\mathrm{P}(Y = j)}{\mathrm{P}(Y = j^{*})}\right) = \alpha_j + \beta_j^{\mathrm{T}} X, \tag{3}$$

with α_j being intercepts for each category and j^* denoting the baseline category against which the log-odds are formed. The latter means that the exp-transformed coefficients indicate whether an independent variable (with all other variables held fixed) makes it more likely $\left(\exp\left(\beta_{jp}\right) > 1\right)$ or less likely $\left(\exp\left(\beta_{jp}\right) < 1\right)$ that the response variable falls into a category j compared to the baseline category. The baseline-category logit model is fitted using the same set of independent variables as with the ordinal logit model.

An important assumption of many regression models including the ones used here is that of independence. Our dataset includes observations from different respondents, all of whom lived in Lisbon at the time of responding, but who

Table 2. Spatial autocorrelation results for the DLC_i and DLS_i scores. The reported *p* values have been determined for two-sided tests and under the randomisation assumption (for the latter, see Cliff and Ord 1981).

Score	Spatial weights	Moran's *I*	*p*-value
DLC_i	5-NN	0.04	0.20
DLC_i	10-NN	0.03	0.21
DLS_i	5-NN	0.03	0.36
DLS_i	10-NN	0.03	0.14

completed our survey without mutual interference. However, the fact that the respondents lived in Lisbon at the same time means that they were partially exposed to similar environmental conditions, lifestyles, and other characteristics derivative of the city. The latter may have led to spatial autocorrelation in the collected responses. Using global Moran's *I* (Getis 2010; Westerholt 2022) in conjunction with 5 and 10-nearest-neighbour weights (to account for different scales) between the centroids of the respective shapes, the results show no significant autocorrelation in the DLC_i and DLS_i scores (Table 2). Another important assumption is the absence of multicollinearity in the independent variables. We test this using generalised variance inflation factors (see Fox and Monette 1992) for all regressors included in the proportional-odds models.[11] This is necessary because some of our regressors are ordinal variables and standard variance inflation factors would not reflect their combined inflationary tendency, but separately for the individual categories. The variance inflation factors do not suggest problems for most variables, but show high values above 10 for the two calculated geometric complexity scores across all models. Therefore, we de-correlated both using principal component analysis (Lafi and Kaneene 1992). One of the resulting projected scores (referred to as pca2 hereafter) reflects above 90% of the total variability shared between both original scores and is strongly associated with the number of contour points. The second projected score (pca1) represents all remaining variability in our complexity modelling that cannot be explained by numbers of points but is attributable to other aspects like the level of care in drawing, etc. After these steps, our models adequately fulfil the assumptions of ordinal logistic regression.

4. Results

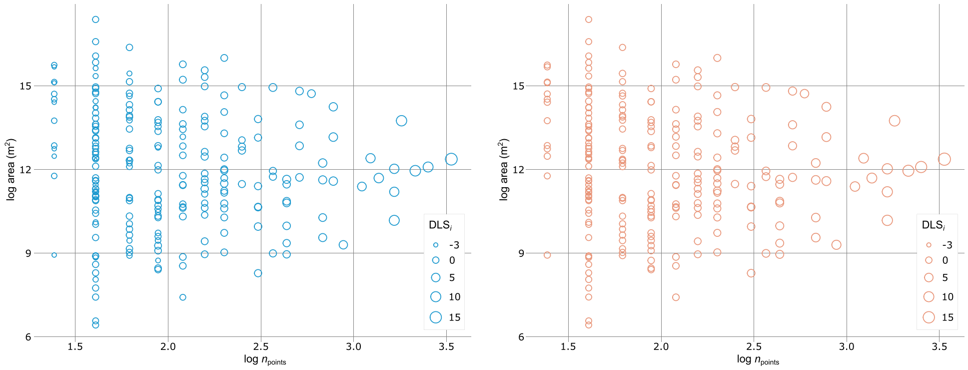
This section provides a description of the shape complexity assessment and a discussion of the modelling results. Before discussing the latter in Section 4.2, we provide the reader with an overview of the two types of assessed complexity in Section 4.1. This overview includes maps to support the identification of potential geographic patterns and some basic statistics allowing for a better numerical comprehension of the two variables. This is then followed by a discussion of the modelling results obtained in conjunction with our operationalisation of sense of place. We finally discuss some limitations of our approach in Section 4.3.

4.1. *Shape complexities*

Adequate contextualisation of the modelling results presented below requires a good understanding of the nature of both types of shape complexity (which are also both reflected in the combined variable employed in the modelling step). Figure 4 shows the histograms of the two standardised shape complexity measures DLC_i (Figure 4(a)) and DLS_i (Figure 4(b)). None of the histograms provides clear indications of symmetry. Therefore, the arithmetic means of the underlying sample values may be of limited informative value, and we have therefore standardised the variables by centring them around their medians and scaling them by their median absolute deviations. The values shown in the histograms are therefore expressed as multiples of the median of the absolute deviations from the sample median and not as multiples of standard deviations (as would be the case with the more common form of z-score standardisation). These histograms are supported by maps shown in Figure 6, which provide an idea of the geographical distribution of both the sampled polygons and their respective shape complexity scores.

The contour-related DLC_i values show a long-tail behaviour towards the right tail and an accumulation in the lower to middle value range of their distribution. The histogram in Figure 4(a) shows a peak at (non-standardised) values between 12 and 13 (around 0 in the plot of standardised values). This peak is below the arithmetic mean of 13.84 and includes the median of 12.92. The decline to either side is sharp, while it appears more abrupt towards the lower end. Since DLC_i is supported on the semi-infinite interval $[0, \infty)$, one could have intuitively expected an accumulation of values near the lower bound 0 of the support. However, looking at the contours shown in Figure 6(a), it is noticeable that most contours with low complexity are triangular, quadrangular, or similar in shape. Recall that the null model to which the contours are compared assumes a smooth contour. The shapes described here are not particularly smooth but, although they are relatively simple, still have an edgy character. This explains why the histogram does not peak near the lower bound, but slightly away from it. This characteristic is also captured in Figure 5(a), which juxtaposes the DLC_i scores with the numbers of contour points and the areas covered by the polygons drawn. The DLC_i values are not significantly correlated with contour length ($r = 0.07$), but strongly associated with the number of contour points ($r = 0.94$). The right-hand side of the empirical distribution is characterised by outliers. These range up to DLC_i values above 40 (more than 16 times the median absolute deviation) and indicate that some respondents drew rather complex footprints of their most important places. We therefore have two types of contours: simple ones, which are characterised by edgy but simple contour lines, and complex ones causing a long right tail in the DLC_i empirical distribution.

The DLS_i values, which describe the complexities of the skeletons, are closely linked to the contour-related DLC_i values. Both complexity measures are strongly and significantly correlated ($r = 0.944$, $p \leq 0.01$), which is why we de-correlate them for the regression modelling (as outlined inSection 3.3). The strong correlation indicates an interesting correspondence: respondents who draw complex contours also tend to draw more complex shapes overall. This finding is easy to explain for the most complex shapes drawn but not trivial in a general sense, as it would be quite possible to draw a simple overall shape (e.g. a more or less linear polygonal structure) but with complex, sharply angled contour



(a) Contour complexity

(b) Skeleton complexity

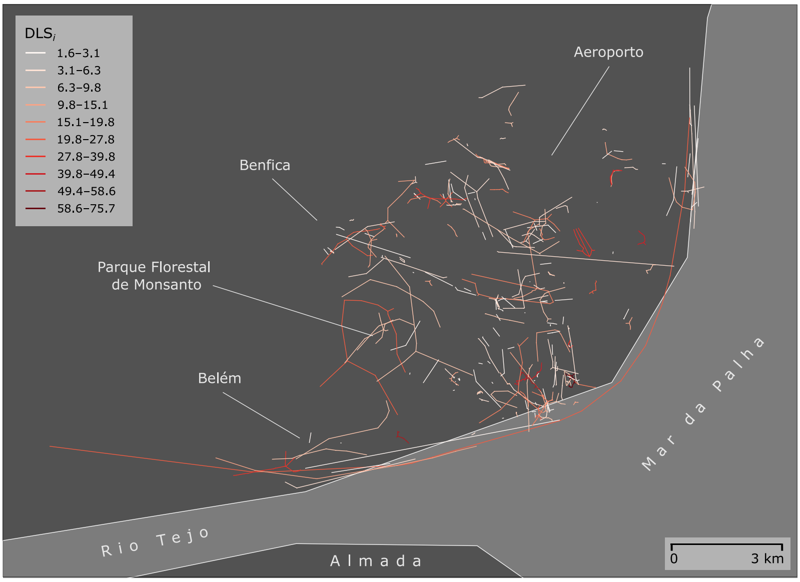
Figure 5. Scatterplots juxtaposing polygon areas, the number of contour points, and the respective complexity scores. The polygon areas and the numbers of points are presented on a logarithmic scale for improved visualisation. The complexity scores are centred on their respective sample medians and scaled according to their median absolute deviations.

line segments. The strong correlation shows that, at least in our sample, those who draw complex overall shapes also tend to draw more complex contour lines. Apart from this, we see a weak correlation between DLS$_i$ and skeleton length ($r = 0.21$, $p \leq 0.01$), which, however, does not appear to be very systematic when the two variables are plotted against each other (not shown due to length restrictions) but driven by a few outliers. This weak correlation can be explained by the fact that very small and simple polygons tend to condense into simple single-line skeletons, of which there are several in the map, as shown in Figure 6(b). Looking at the histogram shown in Figure 4(b), the lower end of the distribution shows a different pattern than for DLC$_i$. A large number of observations accumulate in the region near the lower bound of 0, which can be explained by the single-line skeletons combined with sprout numbers close to their expectation, as described above. The right tail of the histogram shows some outliers in a similar order of magnitude as observed for DLC$_i$. These outliers strongly coincide with those of DLC$_i$ and form the most strongly correlated subset of the value range. This subgroup of corresponding high DLC$_i$ and DLS$_i$ values can also be identified when comparing Figures 5(a) and 5(b).

4.2. *Modelling results*

The results of both types of logit modelling are described and discussed below. For the ordinal proportional-odds logit modelling, summaries of the results are presented in the Tables 3–5, which are divided into sub-tables presenting the results for the corresponding ordinal sense-of-place variables. In each table, the contributions of the ordinal independent variables are presented in terms of their linear, quadratic, cubic, and quartic influences on all categories, thereby recognising their ordinal nature (rather than using their categories independently). Thereby, the results for variables with the suffix '.L' indicate the impact of linear trends across the ordered categories, the '.Q' component provides the influence of possible quadratic trends (i.e. acceleration or deacceleration), and so on. For each fitted model, the results of Hosmer–Lemeshow

(a) Contour complexity scores DLC$_i$



(b) Skeleton complexity scores DLS$_i$

Figure 6. Overview maps of the two different calculated shape complexity scores.

tests (which are based on the differences between fitted and observed counts per category of the dependent variable, see Fagerland and Hosmer 2012) and Nagelkerke pseudo-R^2 values (which represent the surplus in explanatory power of the models compared to models without regressors, see Nagelkerke 1991) are also reported and interpreted in tandem. In contrast, reporting the results of the baseline-category logit modelling yields more extensive tables due to the four categories looked at for each of

Table 3. Results of the ordinal proportional-odds logit regression modelling for the place attachment variables. IV = independent variable, η_p = p-th regression coefficient, η_p^{exp} = p-th regression coefficient expressed as proportional odds ratios, SE = standard error, t = test statistic for the η_p values, $\hat{p}$ = approximated pseudo p-values

IV	η_p	η_p^{exp}	SE	t	$\hat{p}$
so.L	2.24	9.38	0.80	2.79	$\leq 0.01^{***}$
so.Q	-0.43	0.65	0.69	-0.63	0.53
so.C	0.07	1.07	0.50	0.14	0.89
so.4	-0.11	0.90	0.35	-0.31	0.76
us.L	1.10	3.01	0.71	1.55	0.12
us.Q	-0.04	0.96	0.58	-0.07	0.94
us.C	0.04	1.04	0.46	0.08	0.93
us.4	0.30	1.35	0.36	0.84	0.40
ae.L	0.53	1.70	0.87	0.61	0.54
ae.Q	0.83	2.29	0.72	1.15	0.25
ae.C	0.02	1.02	0.49	0.04	0.97
ae.4	0.01	1.01	0.33	0.04	0.97
ac.L	0.97	2.63	0.63	1.52	0.13
ac.Q	0.41	1.51	0.55	0.75	0.45
ac.C	0.13	1.14	0.45	0.29	0.77
ac.4	-0.26	0.77	0.36	-0.72	0.47
pca1	0.02	1.02	0.10	0.24	0.81
pca2	0.00	1.00	0.57	0.01	1.00

Hosmer–Lemeshow: $\chi^2_{35} = 83.62, p \leq 0.01$
Nagelkerke $R^2 = 0.38$

(a) PA1: Easing

IV	η_p	η_p^{exp}	SE	t	$\hat{p}$
so.L	1.94	6.93	0.81	2.39	0.02^{**}
so.Q	-0.21	0.81	0.70	-0.31	0.76
so.C	0.02	1.02	0.51	0.04	0.97
so.4	-0.19	0.83	0.36	-0.53	0.60
us.L	0.40	1.50	0.67	0.60	0.55
us.Q	0.65	1.92	0.56	1.16	0.24
us.C	-0.06	0.94	0.46	-0.13	0.90
us.4	0.09	1.09	0.36	0.24	0.81
ae.L	0.68	1.96	0.83	0.81	0.42
ae.Q	1.22	3.39	0.71	1.73	0.08^{*}
ae.C	0.14	1.15	0.48	0.29	0.77
ae.4	-0.22	0.80	0.33	-0.67	0.50
ac.L	1.57	4.80	0.64	2.46	$\leq 0.01^{***}$
ac.Q	-0.58	0.56	0.55	-1.04	0.30
ac.C	0.60	1.83	0.44	1.37	0.17
ac.4	0.11	1.12	0.36	0.32	0.75
pca1	0.09	1.09	0.09	0.92	0.36
pca2	1.09	2.98	0.57	1.91	0.06^{*}

Hosmer–Lemeshow: $\chi^2_{35} = 42.30, p = 0.19$
Nagelkerke $R^2 = 0.40$

(b) PA2: Joy

IV	η_p	η_p^{exp}	SE	t	$\hat{p}$
so.L	1.10	3.00	0.75	1.46	0.14
so.Q	-0.01	0.99	0.62	-0.02	0.98
so.C	-0.34	0.71	0.45	-0.75	0.45
so.4	0.18	1.20	0.33	0.56	0.57
us.L	0.74	2.11	0.68	1.10	0.27
us.Q	-0.28	0.75	0.55	-0.52	0.60
us.C	0.55	1.74	0.44	1.27	0.21
us.4	-0.66	0.52	0.35	-1.89	0.06^{*}
ae.L	0.03	1.03	0.87	0.03	0.97
ae.Q	0.95	2.58	0.72	1.32	0.19
ae.C	0.19	1.21	0.47	0.40	0.69
ae.4	-0.06	0.94	0.32	-0.18	0.85
ac.L	1.29	3.64	0.71	1.83	0.07^{*}
ac.Q	0.02	1.03	0.59	0.04	0.97
ac.C	0.52	1.69	0.46	1.13	0.26
ac.4	-0.20	0.82	0.35	-0.57	0.57
pca1	0.09	1.10	0.09	1.05	0.29
pca2	1.00	2.72	0.53	1.88	0.06^{*}

Hosmer–Lemeshow: $\chi^2_{35} = 49.83, p = 0.05$
Nagelkerke $R^2 = 0.28$

(c) PA3: Preference

so = sociability, us = usability, ae = aesthetic assessment, ac = accessiblity, pca = footprint shape complexity scores

Table 4. Results of the ordinal proportional-odds logit regression modelling for the place identity variables. IV = independent variable, η_p = p-th regression coefficient, η_p^{exp} = p-th regression coefficient expressed as proportional odds ratios, SE = standard error, t = test statistics for the η_p values, $\hat{p}$ = approximated pseudo p-values

IV	η_p	η_p^{exp}	SE	t	$\hat{p}$
so.L	1.64	5.13	0.78	2.10	0.04^{**}
so.Q	-0.02	0.98	0.63	-0.02	0.98
so.C	-0.23	0.80	0.47	-0.48	0.63
so.4	-0.09	0.92	0.34	-0.26	0.80
us.L	-0.21	0.81	0.65	-0.32	0.75
us.Q	0.63	1.87	0.53	1.19	0.24
us.C	0.09	1.10	0.43	0.22	0.83
us.4	-0.38	0.68	0.35	-1.08	0.28
ae.L	2.08	8.02	0.74	2.83	$\leq 0.01^{***}$
ae.Q	-0.12	0.89	0.60	-0.20	0.84
ae.C	0.65	1.91	0.43	1.50	0.13
ae.4	-0.15	0.86	0.31	-0.47	0.64
ac.L	-0.16	0.85	0.65	-0.25	0.80
ac.Q	0.65	1.92	0.57	1.15	0.25
ac.C	-0.10	0.90	0.45	-0.24	0.81
ac.4	0.31	1.37	0.35	0.90	0.37
pca1	0.17	1.18	0.09	1.86	0.06^{*}
pca2	1.08	2.94	0.55	1.98	0.05^{**}

Hosmer–Lemeshow: $\chi^2_{35} = 39.98, p = 0.26$
Nagelkerke $R^2 = 0.33$

(a) PI1: Personification

IV	η_p	η_p^{exp}	SE	t	$\hat{p}$
so.L	2.14	8.49	0.82	2.60	$\leq 0.01^{***}$
so.Q	-0.81	0.44	0.68	-1.19	0.24
so.C	0.11	1.11	0.49	0.22	0.82
so.4	-0.26	0.77	0.34	-0.76	0.45
us.L	0.67	1.95	0.68	0.98	0.32
us.Q	0.72	2.05	0.55	1.30	0.20
us.C	0.09	1.09	0.45	0.19	0.85
us.4	-0.19	0.83	0.35	-0.53	0.60
ae.L	1.00	2.71	0.79	1.27	0.20
ae.Q	0.40	1.49	0.66	0.61	0.54
ae.C	0.46	1.59	0.46	1.02	0.31
ae.4	-0.35	0.71	0.32	-1.10	0.27
ac.L	0.78	2.19	0.69	1.13	0.26
ac.Q	-0.21	0.81	0.61	-0.35	0.73
ac.C	0.34	1.41	0.46	0.74	0.46
ac.4	0.03	1.03	0.35	0.10	0.92
pca1	0.09	1.10	0.09	1.00	0.32
pca2	1.15	3.16	0.57	2.02	0.04^{**}

Hosmer–Lemeshow: $\chi^2_{35} = 31.09, p = 0.66$
Nagelkerke $R^2 = 0.37$

(b) PI2: Oneself

IV	η_p	η_p^{exp}	SE	t	$\hat{p}$
so.L	2.09	8.10	0.79	2.66	$\leq 0.01^{***}$
so.Q	-0.80	0.45	0.65	-1.22	0.22
so.C	0.08	1.09	0.48	0.17	0.86
so.4	-0.10	0.90	0.34	-0.30	0.76
us.L	0.33	1.39	0.66	0.49	0.62
us.Q	0.77	2.15	0.54	1.42	0.15
us.C	0.22	1.25	0.43	0.52	0.60
us.4	-0.42	0.66	0.35	-1.20	0.23
ae.L	1.83	6.21	0.73	2.50	$\leq 0.01^{***}$
ae.Q	-0.05	0.95	0.61	-0.09	0.93
ae.C	1.15	3.16	0.44	2.61	$\leq 0.01^{***}$
ae.4	-0.60	0.55	0.31	-1.92	0.05^{**}
ac.L	0.58	1.78	0.69	0.83	0.40
ac.Q	0.13	1.14	0.59	0.22	0.83
ac.C	-0.19	0.83	0.46	-0.41	0.68
ac.4	0.20	1.22	0.36	0.55	0.58
pca1	0.06	1.06	0.09	0.60	0.55
pca2	1.49	4.44	0.57	2.63	$\leq 0.01^{***}$

Hosmer–Lemeshow: $\chi^2_{35} = 61.08, p \leq 0.01$
Nagelkerke $R^2 = 0.39$

(c) PI3: Materialisation

so = sociability, us = usability, ae = aesthetic assessment, ac = accessiblity, pca = footprint shape complexity scores

Table 5. Results of the ordinal proportional-odds logit regression modelling for the place dependence variables. IV = independent variable, η_p = p-th regression coefficient, $\eta_p^{\exp}$ = p-th regression coefficient expressed as proportional odds ratios, SE = standard error, t = test statistics for the η_p values, $\hat{p}$ = approximated pseudo p-values

IV	η_p	$\eta_p^{\exp}$	SE	t	$\hat{p}$
so.L	0.95	2.59	0.77	1.23	0.22
so.Q	-0.05	0.95	0.63	-0.08	0.93
so.C	-0.17	0.85	0.47	-0.36	0.72
so.4	-0.29	0.75	0.34	-0.88	0.38
us.L	1.10	3.01	0.69	1.60	0.11
us.Q	0.19	1.21	0.56	0.34	0.74
us.C	0.23	1.26	0.45	0.51	0.61
us.4	0.44	1.55	0.35	1.25	0.21
ae.L	0.39	1.48	0.78	0.50	0.62
ae.Q	0.37	1.45	0.67	0.55	0.58
ae.C	0.48	1.61	0.46	1.04	0.30
ae.4	-0.54	0.58	0.32	-1.69	0.09*
ac.L	1.08	2.95	0.65	1.66	0.10*
ac.Q	-0.34	0.71	0.56	-0.60	0.55
ac.C	0.02	1.02	0.44	0.04	0.97
ac.4	0.25	1.29	0.34	0.73	0.47
pca1	0.00	1.00	0.09	-0.03	0.98
pca2	0.86	2.35	0.52	1.63	0.10*

Hosmer–Lemeshow: $\chi^2_{35} = 32.37, p = 0.60$
Nagelkerke $R^2 = 0.26$

(a) PD1: Suitability

IV	η_p	$\eta_p^{\exp}$	SE	t	$\hat{p}$
so.L	-0.40	0.67	0.75	-0.53	0.59
so.Q	0.64	1.90	0.61	1.05	0.30
so.C	-0.54	0.59	0.45	-1.20	0.23
so.4	0.05	1.05	0.32	0.15	0.88
us.L	1.03	2.81	0.69	1.49	0.14
us.Q	0.58	1.79	0.58	1.01	0.31
us.C	-0.15	0.86	0.44	-0.34	0.73
us.4	0.12	1.13	0.34	0.35	0.73
ae.L	-0.23	0.79	0.78	-0.30	0.77
ae.Q	0.44	1.56	0.67	0.66	0.51
ae.C	0.34	1.40	0.47	0.73	0.47
ae.4	-0.17	0.84	0.31	-0.55	0.58
ac.L	0.76	2.15	0.65	1.17	0.24
ac.Q	-0.54	0.58	0.57	-0.95	0.34
ac.C	0.01	1.01	0.43	0.02	0.99
ac.4	0.11	1.12	0.33	0.33	0.74
pca1	0.03	1.03	0.09	0.36	0.72
pca2	0.54	1.72	0.51	1.05	0.29

Hosmer–Lemeshow: $\chi^2_{35} = 46.46.62, p = 0.09$
Nagelkerke $R^2 = 0.13$

(b) PD2: Uniqueness

IV	η_p	$\eta_p^{\exp}$	SE	t	$\hat{p}$
so.L	0.87	2.38	0.79	1.10	0.27
so.Q	-0.13	0.88	0.63	-0.20	0.84
so.C	-0.29	0.75	0.47	-0.63	0.53
so.4	-0.07	0.93	0.33	-0.21	0.83
us.L	1.47	4.34	0.67	2.19	0.03**
us.Q	0.48	1.62	0.53	0.91	0.36
us.C	-0.17	0.84	0.44	-0.40	0.69
us.4	0.38	1.46	0.35	1.08	0.28
ae.L	0.96	2.62	0.82	1.18	0.24
ae.Q	-0.19	0.83	0.68	-0.27	0.78
ae.C	0.51	1.67	0.46	1.11	0.27
ae.4	-0.49	0.61	0.31	-1.56	0.12
ac.L	0.16	1.18	0.65	0.25	0.80
ac.Q	0.04	1.04	0.56	0.07	0.94
ac.C	-0.04	0.96	0.44	-0.09	0.93
ac.4	-0.03	0.97	0.35	-0.08	0.94
pca1	-0.06	0.94	0.09	-0.72	0.47
pca2	0.52	1.69	0.53	1.00	0.32

Hosmer–Lemeshow: $\chi^2_{35} = 36.64, p = 0.39$
Nagelkerke $R^2 = 0.26$

(c) PD3: Affordance

so = sociability, us = usability, ae = aesthetic assessment, ac = accessiblity, pca = footprint shape complexity scores

the nine variables. The respective tables are thus found in Appendix D. As explained in Section 3, the results of the baseline-category modelling are generally more uncertain than the results of the proportional-odds modelling. The former must therefore be viewed with greater caution than the latter.

4.2.1. *Place attachment*

Our three assessed place attachment variables capture respondents' emotional attachment to their self-declared most important places. The results of the proportional-odds logit modelling summarised in Table 3 show some similarities between the variables 'Joy' (PA2) and 'Preference' (PA3). Both variables capture emotional ties to a place in different ways, with PA2 focusing on whether a place evokes positive/negative emotions, whereas PA3 is linked to a person's disposition towards particular place characteristics and the resulting affection for a place. The pseudo-R^2 values and the Hosmer–Lemeshow tests for both models are acceptable, with the model for PA2 showing a better goodness of fit. Both variables are linearly positively influenced by accessibility (ac.L). The variable 'Joy' is further influenced positively (and strongly in terms of effect size) by the suitability of a place for social interaction (so.L). Both models show a moderately strong influence of footprint shape complexity via pca2, which mainly reflects numbers of contour points. Thus, the more points respondents sketched, the more likely it is that someone rated PA2 and PA3 higher (this interpretation follows from the ordinal nature of the modelling). The latter does not apply to PA1 ('Easing'), for which both the p-values and the effect sizes $\eta_p^{\exp}$ of the shape complexity scores are close to 1. One possible explanation for the deviating model response could lie in a stronger link between the other two dependent variables. One could argue that 'Preference' (PA3) is a partially downstream consequence, or manifestation, of repeated experience of 'Joy' (PA2). Thus, both variables would have a certain relationship with each other, whereas 'Easing' expresses relaxation, which is a different (though related) affect from pleasure (Russell and Pratt 1980). It is also possible that the respondents evaluated the latter dimension more light-heartedly and positively, as one can in principle also feel relaxed (understood in a more colloquial manner) in places with less strong emotional charge. In addition, the model for this variable shows an appropriate pseudo-R^2, but a highly significant Hosmer–Lemeshow test. The results should therefore be treated with caution.

The results of the baseline-category logit modelling are offered in Tables D1, D2, and D3 (all in Appendix D). They largely confirm the results reported above, but provide further detail. For PA2, the pca2 variable is significant when comparing 'strongly agree' with the baseline category 'neutral', but not for other comparisons. This means that the averaged result reported above is mainly driven by the very strong expressions of 'Joy'. However, there is also a non-significant but rather strong negative effect when comparing 'disagree' with the baseline category, which might be an interesting indication worth reporting. Apart from the complexity scores, the disaggregated results confirm the findings for accessibility (ac.L), but show that these mainly apply to above-average 'Joy' scores. The latter is also true for a quadratic, accelerating trend in aesthetic place evaluation (ae.Q), which is a further confirmation of the ordinal results reported above. In contrast, the influence of sociability is not confirmed. This variable shows strong but fluctuating effect sizes for some categories, which could explain the global trend reported above. Regarding PA3 (‘Preference’), the baseline-category logit results show that pca2 mainly has a negative effect on the ‘disagree’ category. However, no significant positive effect is observed for high values in the dependent variable. In addition, we can notice a highly significant impact of pca1 on ‘agree’ scores, though the effect size is not notably strong. Beyond footprint complexity, higher order trends (.C, .4) are sometimes flagged as significant, but these are rather difficult to interpret as the results are not very systematic, so we refrain from interpretations at this point. The results obtained for PA1 confirm the results reported in the previous paragraph. Sociability strongly dominates for the categories ‘agree’ and ‘strongly agree’, but not for others. The Hosmer–Lemeshow tests are highly significant for all models, which is probably an effect of the reduced sample size per category. In contrast, the Nagelkerke pseudo-R^2 values are between 0.4 and 0.6, which is an improvement over the averaged ordinal models reported above.

4.2.2. *Place identity*

The results of the proportional-odds logit modelling for place identity are found in Table 4. All three variables capture the extent to which someone associates their own personal characteristics with meaningful places. The variables PI1 (‘Personification’) and PI3 (‘Materialisation’) are quite close to each other and differ primarily in the degree of abstraction required by the respondents. PI1 is more focused on very personal, individual characteristics, while PI3 requires a step of abstraction through categorisation into personality types. The results reported in the Tables 4(a) and 4(c) thus show similarities. Both variables are influenced by the aesthetic qualities of places, for which we can thus recognise a role in the process of people’s personal relationship with urban areas. The cubic component of the aesthetics variable furthermore indicates a strong upward slope across the analysed aesthetics categories. The result for PI2 (‘Oneself’) in Table 4(b) differs slightly from the other two, as aesthetics does not appear to play a major role. One reason for this could be the opposite nature of the underlying question, in which respondents are asked to relate their own personality to an area (in PI1 and PI3, the areas must be related to oneself). Another reason could be that some respondents may have misunderstood the possibility of ‘being themselves’ as ‘letting go’ or ‘relaxing’, which could have led to incorrect answers. There is a significant linear trend in sociability for all three variables. However, inspection of the results on a map suggests that this is more likely to be a secondary effect caused by the fact that many of the higher scores for place identity are found in dense urban areas such as Benfica and the Old Town, which also have high scores for sociability. The complexity of the footprint shape is also significant for all variables, with the highest effect size regarding pca2 for PI3 related to personality types. In contrast, the lowest pca2 effect size is found for the PI1 variable that captures the most direct correspondences between individuals and places. This could indicate that people have a stronger place-related intuition for more abstract personality categories into which they categorise themselves than for more complex and unspecified characteristics. In terms of other forms of shape complexity, beyond the number of points sketched, only PI1 (‘Personification’) is found to be significantly related to pca1. This is interesting as it suggests a stronger link between potentially more nuanced and subtle aspects of form complexity and the evaluation of place identity with a more personalised, intimate, individual character. Again, the model fit diagnostics show a mixed picture, with the Nagelkerke pseudo-R^2

values being acceptable, but many Hosmer–Lemeshow tests being significant. Thus, as expected, there is most likely some uncertainty in the models.

The results of the baseline-category logit modelling for place identity (Tables D4, D5, and D6) provide further evidence of the differences between the three different types of aspects captured in PI1, PI2, and PI3. The importance of pca2 (i.e. the variable related to number of contour points) is only confirmed for PI2 ('Oneself') and PI3 ('Materialisation'), but not for PI1 ('Personification'). The influence of pca2 is dominated by the two highest categories ('agree' and 'strongly agree') through increasing their odds. Interestingly, the results for the lowest categories ('disagree' and 'strongly disagree') are not noteworthy in terms of *p*-values and only marginally in terms of effect size. These results seem to confirm the indication reported above that people seem more likely to associate their important places with personality categories (PI3) than with unspecified characteristics (PI2). Another interesting result is that the strong influence of aesthetic place qualities found for PI1 and PI3 is not confirmed by the category-wise modelling. Instead, some significant influences are reported for fourth-order trends for both aesthetics and accessibility. However, as mentioned above, these are difficult to interpret in isolation without lower order trends also being significant. In contrast to the influences determined for pca2, pca1 is significantly related to 'agreement' and 'disagreement' categories for PI1, and thus on both sides of the neutral category. It is noteworthy that the largest effect is associated with the lowest category ('strongly disagree') and is negative. This shows that, beyond mere point counts, people seem to draw less complex polygons for places that they do not think are related to their identity. Positive effects beyond the neutral category, by contrast, are more limited in effect size, though the impact pca1 has on 'agree' is flagged as strongly significant. The Nagelkerke pseudo-R^2 values are acceptable for all models, but the Hosmer–Lemeshow tests are significant.

4.2.3. *Place dependence*

The place dependence variables represent different aspects of the added value of opportunities offered by meaningful places. PD1 ('Suitability') and PD3 ('Affordance') ask about the ability of places to facilitate meaningful activities, with PD1 referring to the degree of supportive capabilities of a place and PD3 emphasising the more general affordance of facilitating meaningful activities in the first place. In contrast, PD2 ('Uniqueness') asks about the degree to which the places deemed most important are superior to others in this respect. The proportional-odds logit model results show a mixed picture (Table 5). While, according to the Hosmer–Lemeshow tests, these models generally appear to be better suited than the models for other variables, the Nagelkerke pseudo-R^2 values are comparatively lower. Not surprisingly, although usability (us.L) is significant in only one model (PD3), it consistently shows relatively low *p*-values (close to 0.1) and relatively large effect sizes in all three models. Given the uncertainties in our modelling, it is therefore reasonable to assume a tendency, which seems reasonable in light of the meaning of place dependence we employ for this study variable. For PD1, there is also a significant linear trend across the accessibility categories (ac.L), which is also plausible as accessibility may be one of the supporting capabilities of place that this variable is intended to capture. The only model for which footprint shape complexity (pca2) is significant is PD1, however the *p*-value is not very small and the effect size is smaller than in most of the other models described above. Shape complexity appears to have little effect on the other place dependence variables.

The results of the baseline-category modelling (Tables D7, D8, and D9) shed further light on the results reported above. Regarding PD1 and PD3, the pca2 shape complexity variable capturing numbers of contour points has a negative significant effect for the disagreement-related categories. At the same time, pca1 (capturing shape complexity beyond mere numbers of points) yields a significant positive impact on 'disagreement' and 'strong disagreement' and for the same variables. This contrasting effect of positive influence for pca1 and negative influence for pca2 on disagreement may have led to the somewhat uncertain but significant result for shape complexity on PD1 in the previous paragraph. In particular, the positive effect of pca1 on the log odds of the 'disagree' categories appears to be counter-intuitive. However, this effect is consistent for PD1 and PD3, two categories that are similar in that they assess the utility of a place (as opposed to PD2, which is about comparing places regarding utilitarian aspects). One possible explanation for this behaviour could therefore be that some people in our sample have identified their places as meaningful and important in the sense of utilitarian aspects such as shopping, dealing with administrative matters, etc. Such places are indeed meaningful and important. While such places may be important, they could differ from other types of places in terms of intimate relationships and bonding, which could have led to the results reported above. For PD2, the disaggregated, category-by-category modelling shows that while usability is not linearly correlated, it shows an accelerating trend in the odds for 'agree', while it is linearly negatively correlated (but not significant) for 'disagree'. In contrast to the proportional-odds modelling, the results for the baseline-category modelling show a significant negative effect of shape complexity (pca2) for the 'disagree' category for PD3. These models should also be viewed with some caution (all Hosmer–Lemeshow tests are significant), although the Nagelkerke pseudo-R^2 values are slightly more favourable than for the results described in the previous paragraph.

4.3. *Limitations*

The methodological approach used is subject to certain limitations. One of these limitations is that we do not have information about the acquisition scale of the polygons. Some of the respondents might have zoomed in before drawing, while others might have chosen a coarser scale of recording. The reason why this is a limitation is that the acquisition scale might have influenced the geometric qualities of the footprints collected, an effect that has been observed in the context of volunteered geographic information (Touya and Reimer 2015). However, even if different mapping scales are reflected in our database, they should occur randomly with respect to the data collected with the survey as there is no reason to believe that only respondents contributing high or low-complexity polygons have zoomed in or out, which means that no systematic effects on our correlative assessment should be discernible. Researchers attempting to replicate our research in other geographical areas should record the acquisition scale via the web mapping technology they use. Another limitation is that all our participants have taken part in public participation activities in the past. It is well known that these types of activities attract people according to their language skills, socio-economic and demographic status, technical skills (especially in online participation), and other factors (Lawson et al. 2022). Thus, despite the good fit of our participant group with some general Lisbon population characteristics, our results may not be fully representative of all branches of society. However, as our sampling technique allowed us to engage with a reasonable number of people living in the city of Lisbon, we argue that our approach is useful as long as the limitations outlined are taken into account and no undue inferences are made. A third and similar limitation is that we did not capture personality traits (McCrae 2009) to identify, for example, someone as pedantic or perfectionist in nature. Such traits may further interact with underlying values (see Parks-Leduc, Feldman, and Bardi 2015) and could have affected the geometric properties of the mapped polygons. However, reliably identifying these traits would have required an extensive experimental design, which could not only have affected our participants' willingness to participate but would also have reduced our sample size due to the effort required. Future research on spatial footprints of sense of place could therefore be conducted on a smaller scale and allow for more in-depth interaction with individual participants. Further, as mentioned above, there is no perfect model for the type of information at hand. Our tandem of two models can therefore only provide indications (possibly strong indications if both models agree), but no definitive conclusive results. Our aim is therefore to gather meaningful evidence from our sufficiently large sample (for which our approach is suitable), on the basis of which more in-depth analyses of smaller datasets from fewer respondents can be conducted in follow-up research. Another interesting aspect that we do not address in the present investigation is the extension of place-making to the digital domain (see Basaraba 2023; Halegoua and Polson 2021, for a recent overview and special issue). This could also have an impact on how people translate places into geometric representations and should be explored in future research. Finally, and inherent to our case study approach, our findings are based on data from a single city. Future studies in other cities, including variations of different cultural regions, are therefore necessary to complement the results put forward in this article.

5. Discussion and conclusions

Analysing spatial footprints of places in a meaningful way requires an understanding of how such reductionist representations relate to place. In this article, we analysed possible relationships between sense of place and the shape complexity of corresponding spatial footprints. Data were collected using a web-mapping-based survey in which participating Lisbon residents could draw polygons of their self-selected most important places on a map. This was followed by a series of statements to operationalise sense of place. The analysis then started from a null hypothesis of smooth contours and employed two statistical measures of shape complexity to assess both the contours and the polygonal shapes overall. The relationships between sense of place and these shape complexities were established using two types of logit regression models. Our results show that shape complexity has little to do with utilitarian place dependence, but exhibits some strong associations with attachment and identity-related aspects of place.

The ways in which people sketch footprints thus reflect relevant features of the underlying sense of place.

Looking at the results of the three sense-of-place dimensions combined, we can conclude that the variables reflecting a deeper engagement with places are related to aspects of complexity beyond mapped numbers of points. For place attachment, we see that the variable pca1 (that is, that variation shared between the two complexity measures that does not correlate with the number of contour points) is significantly and positively associated with the statement that indicates places as favoured (PA3). Of the three place-attachment statements, this is the one whose judgement requires a stronger engagement with the corresponding places than the others. A similar pattern emerges for the dimension of place identity. Here we find a negative relationship for disagreement and a positive relationship for agreement with the variable PI1, which presupposes a stronger association at a detailed level between personality and place. These findings show strong indications of a relationship between either the general level of detailed knowledge about or affiliation with a place, or the reflection of a place at the moment of answering the survey. Both are possible and would need to be investigated more specifically. A clearer determination of such a distinction would require more detailed knowledge of the factors that feed into the variable pca1 that is used here as an aggregate. For many other place attachment and place identity variables, the number of contour points set also plays an important role. We can interpret this as follows: Increasing the number of points can be seen as a weak level of complexity increase, as more points in the present study design implies setting a higher number of detail or corner points of the mapped territories. At a certain stage of place engagement, more sophisticated forms of complexity take over in the geometric place representation, such as a more precise delineation of spatial details, better recall of more precise shape trajectories, among other aspects. These interpretations may be supported by recent findings on the relationship between the amount of semantic information in visual scenes and the contraction and expansion of scene boundaries. Greene and Trivedi (2023, 454) have found that "[…] semantic (but not visual) information predicted whether a scene's boundaries would contract or expand in memory". In our study, contracting may imply concave contours (which are often rated as more complex). Moreover, the amount of semantic information here implies a greater degree of meaningful and intimate prior experience with places. These aspects may partly explain our conclusion drawn above.

The results presented above can be related to the psychological literature on representational complexity. In recent studies, Sun and Firestone (2022a) and Sun and Firestone (2022b) have shown that the complexity with which people represent visual stimuli (including polygons) exhibits an inverted U-shaped graph when plotted against the complexity assessments of the features under consideration (which included polygons). An important difference to our study is that the respondents did not have to sketch themselves but interpreted predefined polygons and therefore had to describe features that might be more complex than the respondents would have chosen themselves under free choice. However, evidence was found of a correspondence between visual processing and the drawing of visual stimuli (C. P. Davis, Morrow, and Lupyan 2019; Fan, Yamins, and Turk-Browne 2018). It is therefore plausible that our study complements the outlined findings in two ways: we present a geographical scenario that goes beyond the abstract (non-contextualised) shapes presented to the subjects in Sun and Firestone (2022a) and Sun and Firestone (2022b), and we extend the complexity view towards sense of place and thus towards a complex process upstream of visual representation. These aspects are usually not taken into account in depth in existing studies and shall be considered in future research.

Another interesting aspect that emerged in our study is the prevalence of quadrilateral polygons mapped by our respondents. These polygons are particularly associated with lower complexity scores and lower sense of place scores, but are abundant across the spectrum. An intuitive explanation for this effect is that the mapping function of our survey to some extent invited respondents to choose these types of shapes if they did not want to spend too much time and effort completing the survey. However, it has also recently been shown that humans process quadrilateral shapes differently than animals: "[…] in humans only, regular quadrilaterals such as squares, rectangles or parallelograms (which can be compressed in the present language) are easier to perceive than less regular ones" (Sablé-Meyer et al. 2022, 19; see also Sablé-Meyer et al. 2021). Again, these findings are based on the interpretation of visual stimuli and therefore differ slightly from our study design. Nevertheless, we speculatively argue that our respondents may have given so many self-reported quadrilateral shapes because humans tend to process them with more ease. This would suggest a mechanism similar to vision that is associated with the translation of sense of place into geometric footprints. As this process has been little researched to date, this could provide an interesting link to existing (and also early stage) research.

We have further shown that the utilitarian aspects of sense of place in particular have little to do with shape complexity. This could have various reasons. Westerholt, Acedo, and Naranjo-Zolotov (2022) used Google Places to show that the presence of supposedly anonymous shopping opportunities and mundane facilities in particular has a negative correlation with place identity aspects. We show that similar findings appear to be evident in connection with shape complexity, as such places are presumably associated more with place dependence than with the more personal dimensions of place. There could be several possible explanations for this. One reason for the marginal association could be the everyday nature of utilitarian places. The habitualised processes and movements at retail venues, for example, can certainly shape the character of a place to a certain extent (Cheshmehzangi and Heat 2012; Seamon and Lundberg 2017; Seamon and Nordin 1980). However, it may be that the taken-for-grantedness of such places only comes into play on site, in the concrete experience, and may not be sufficiently personal and effective in terms of identity for the reduction process to corresponding spatial footprints. The above-mentioned mundane nature of the places mentioned, including the associated lack of conscious reflection and thus neglect when drawing polygons, could mean that people only really consciously reflect on these places once they have lost them (Hull, Lam, and Vigo 1994). The ideas of supermodernity (Augé 1995) and placelessness (Relph 1976) – which may be related to the presumed anonymity described above – could also provide important explanations here. Finally, our results regarding the lack of influence of place dependence on shape complexity show that further research is needed into this area.

In 2015, Brown, Raymond, and Corcoran (2015, 50) flagged their article as "the first study to trial the direct mapping of place attachment through an internet-based PPGIS.

[. . .] The construct of place attachment has been the subject of extensive academic and literary attention, but not as a spatially explicit variable in PPGIS." We are still faced with a paucity of directly related studies that focus specifically on place (rather than related yet distinct concepts such as cognitive regions, memories, landscape values, etc.). We also suggest that follow-up studies should focus more on technical aspects such as zoom levels, homogeneity of mapping knowledge (although this might limit the group of potential respondents), among other aspects. Although our results show that spatial footprints can tell us something about place, a more systematic focus on the influence of mapping technology in place mapping would be beneficial for place research in planning and geography. Spatial footprints of sense of place are particularly important for participatory planning, for example through the use of participatory geographic information systems (PPGISs) and participatory mapping initiatives (e.g. Américo da Silva, Kormann da Silva, and Westerholt 2024; Klonner et al. 2021; Knaps et al. 2022; Nummi 2018; Verbrugge et al. 2019). These activities typically aim to support learning about the ideas, feelings, and meanings that people associate with places, and therefore sense of place plays a pivotal role. Moreover, PPGIS and mapping can bridge the gap between planning and the related field of geographic information science. Place is currently gaining prominence in the latter field (Gao 2022; Mocnik 2022; Purves, Winter, and Kuhn 2019; Westerholt 2019; Westerholt, Mocnik, and Comber 2020), which could provide further interesting links to planning in the future.

Notes

1. This sentence should only be understood as a juxtaposition of the two very different concepts of geometric space and meaningful places. People do also often live outside of meaningful places, for example, when moving between them.
2. For discussions of geographic space concepts, see Thrift (2009) and Smirnov (2016).
3. In this study, we only consider physically and mentally unimpaired individuals. Results for participants with other characteristics may differ from ours.
4. Note that we do not discuss mental (or cognitive) mapping in our literature review. The reason for this omission is that mental mapping focuses on topology (Blaser 2000; Tang et al. 2020), and thus the geometric characteristics of mental mapping are often not readily comparable to those of sketch mapping results. For example, Catney, Frost, and Vaughn (2019) show how people inflate the scale of features that are important to them in freeform drawing, which cannot happen in sketch mapping due to the different mapping technique.
5. See also Mocnik (2022), 811 *f.*) for a recent, pointed discussion on the relationship between space and place.
6. Like with place, the precise meanings of space may differ slightly between schools of thought (for a discussion, see Olwig 2006). Therefore, de Certeau (1984, 117) actually speaks of space as practised place, but uses both terms in roughly opposite meanings to those we use for this work.
7. Mapping is used here as a shorthand term for representing places using geospatial coordinates on a map.
8. We have used the PostGIS functions ST_StraightSkeleton and ST_ApproximateMedialAxis. The PostGIS implementation of the latter is based on the straight skeleton, which is why both are in correspondence.
9. Cutpoint coefficients are comparable to intercept coefficients in ordinary linear regression.
10. We only need to model up to the $(J-1)$-th category, as the J-th category would yield an odds denominator of zero, as follows from equation (3).

11. We extend the results of the multicollinearity assessment to the baseline-category logit model. The latter is strongly substratified, so that the corresponding estimates are rather unstable.

Acknowledgements

We are grateful to Mathias Schaefer (TU Dortmund University) for a critical proofread of our manuscript. We further thank Liudmila Slivinskaya (TU Dortmund University) for pointing out additional relevant literature to contextualise this work and Franz-Benjamin Mocnik (Paris Lodron University of Salzburg) for critical comments on a draft of our manuscript. We also thank the anonymous referees for their constructive comments, which contributed to the improvement of the manuscript. Open Access funding is generously provided through the ZBW (Forum 13+) Open Access agreement.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Adams, B., and G. McKenzie. 2012. “Inferring Thematic Places from Spatially Referenced Natural Language Descriptions.” In *Crowdsourcing Geographic Knowledge: Volunteered Geographic Information (VGI) in Theory and Practice*, edited by D. Sui, S. Elwood, and M. F. Goodchild, 201–221. Dordrecht, the Netherlands: Springer. https://doi.org/10.1007/978-94-007-4587-2_12.

Adelfio, M., L. Serrano-Estrada, P. Martí-Ciriquián, J.-H. Kain, and J. Stenberg. 2020. “Social Activity in Gothenburg’s Intermediate City: Mapping Third Places Through Social Media Data.” *Applied Spatial Analysis and Policy* 13 (4): 985–1017. https://doi.org/10.1007/s12061-020-09338-3.

Agnew, J. A. 1987. *Place and Politics: The Geographical Mediation of State and Society*. Boston, MA: Routledge.

Agresti, A. 2012. *Categorical Data Analysis*. 2nd ed. Hoboken, NJ: Wiley.

Aichholzer, O., F. Aurenhammer, D. Alberts, and B. Gärtner. 1995. “A Novel Type of Skeleton for Polygons.” *J.UCS The Journal of Universal Computer Science*, edited by H. Maurer, C. Calude, and A. Salomaa, Vol. 1. 752–761. Berlin/Heidelberg, Germany: Springer. https://doi.org/10.1007/978-3-642-80350-5.

Alavez, J. 2022. “Mapping Intimate Geographies of Grief and Loss.” *Cartographica: The International Journal for Geographic Information & Geovisualization* 57 (4): 270–280. https://doi.org/10.3138/cart-2021-0024.

Alrobaee, T. R., and A. S. Al-Kinani. 2019. “Place Dependence as the Physical Environment Role Function in the Place Attachment.” *IOP Conference Series: Materials Science and Engineering*, Kislovodsk, Russia, 033014. Vol. 698. IOP Publishing.

Américo da Silva, A., I. F. Kormann da Silva, and R. Westerholt. 2024. “Mapping the Margins: A Systematic Scoping Review of the Impact of Digital Mapping on Public Participation in Informal Settlements.” *Habitat International* 147:103040. https://doi.org/10.1016/j.habitatint.2024.103040.

Anderson, B. 2016. *Taking-Place: Non-Representational Theories and Geography*. Oxon, UK: Routledge.

Aram, F., E. Solgi, E. Higueras García, S. D. Mohammadzadeh, A. Mosavi, and S. Shamshirband. 2019. “Design and Validation of a Computational Program for Analysing Mental Maps: Aram Mental Map Analyzer.” *Sustainability* 11 (14): 3790. https://doi.org/10.3390/su11143790.

Augé, M. 1995. *Non-Places: Introduction to an Anthropology of Supermodernity*. London, UK: Verso.

Ayzenberg, V., Y. Chen, S. R. Yousif, and S. F. Lourenco. 2019. “Skeletal Representations of Shape in Human Vision: Evidence for a Pruned Medial Axis Model.” *Journal of Vision* 19 (6): 6. https://doi.org/10.1167/19.6.6.

Azmi, N. F., F. Ahmad, and A. S. Ali. 2014. “Place Identity: A Theoretical Reflection.” *Open House International* 39 (4): 53–64. https://doi.org/10.1108/OHI-04-2014-B0006.

Bae, C. J.-H., and D. R. Montello. 2018. “Representations of an Urban Ethnic Neighbourhood: Residents’ Cognitive Boundaries of Koreatown, Los Angeles.” *Built Environment* 44 (2): 218–240. https://doi.org/10.2148/benv.44.2.218.

Bahrehdar, A. R., O. Koblet, and R. S. Purves. 2019. “Approaching Location-Based Services from a Place-Based Perspective: From Data to Services?” *Journal of Location Based Services* 13 (2): 73–93. https://doi.org/10.1080/17489725.2018.1564383.

Baker, S., Z. Cantillon, and C. Evans. 2023. “Mapping Living Heritage in Kingston and Arthur’s Vale Historic Area, Norfolk Island: Routes, Customary Practices and Emotions.” *The Historic Environment: Policy & Practice* 14 (4): 533–554. https://doi.org/10.1080/17567505.2023.2279386.

Ballatore, A., and S. De Sabbata. 2018. “Charting the Geographies of Crowdsourced Information in Greater London.” *Proceedings of the 21st AGILE Conference on Geographic Information Science*, edited by A. Mansourian, P. Pilesjö, L. Harrie, and R. van Lammeren, 149–168. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-319-78208-9_8.

Ballatore, A., and S. De Sabbata. 2020. “Los Angeles as a Digital Place: The Geographies of User-Generated Content.” *Transactions in GIS* 24 (4): 880–902. https://doi.org/10.1111/tgis.12600.

Basaraba, N. 2023. “The Emergence of Creative and Digital Place-Making: A Scoping Review Across Disciplines.” *New Media & Society* 25 (6): 1470–1497. https://doi.org/10.1177/14614448211044942.

Basu, M., S. Hashimoto, and R. Dasgupta. 2020. “The Mediating Role of Place Attachment Between Nature Connectedness and Human Well-Being: Perspectives from Japan.” *Sustainability Science* 15 (3): 849–862. https://doi.org/10.1007/s11625-019-00765-x.

Bell, S. L., R. Foley, F. Houghton, A. Maddrell, and A. M. Williams. 2018. “From Therapeutic Landscapes to Healthy Spaces, Places and Practices: A Scoping Review.” *Social Science & Medicine* 196:123–130. https://doi.org/10.1016/j.socscimed.2017.11.035.

Best, D., and N. I. Fisher. 1979. “Efficient Simulation of the Von Mises Distribution.” *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 28 (2): 152–157. https://doi.org/10.2307/2346732.

Blaser, A. D. 2000. “A Study of people’s Sketching Habits in GIS.” *Spatial Cognition and Computation* 2 (4): 393–419. https://doi.org/10.1023/A:1015555919781.

Bleisch, S., and D. Hollenstein. 2018. “Exploratory Geovisualizations for Supporting the Qualitative Analysis and Synthesis of Place-Related Emotion Data.” *Cartographic Perspectives* 91 (91): 30–46. https://doi.org/10.14714/CP91.1437.

Boschmann, E. E., and E. Cubbon. 2014. “Sketch Maps and Qualitative GIS: Using Cartographies of Individual Spatial Narratives in Geographic Research.” *Professional Geographer* 66 (2): 236–248. https://doi.org/10.1080/00330124.2013.781490.

Brown, G., C. M. Raymond, and J. Corcoran. 2015. “Mapping and Measuring Place Attachment.” *Applied Geography* 57:42–53. https://doi.org/10.1016/j.apgeog.2014.12.011.

Catney, G., D. Frost, and L. Vaughn. 2019. “Residents’ Perspectives on Defining Neighbourhood: Mental Mapping as a Tool for Participatory Neighbourhood Research.” *Qualitative Research* 19 (6): 735–752. https://doi.org/10.1177/1468794118803841.

Cerveny, L. K., K. Biedenweg, and R. McLain. 2017. “Mapping Meaningful Places on Washington’s Olympic Peninsula: Toward a Deeper Understanding of Landscape Values.” *Environmental Management* 60 (4): 643–664. https://doi.org/10.1007/s00267-017-0900-x.

Chapin, F. S., III, and C. N. Knapp. 2015. “Sense of Place: A Process for Identifying and Negotiating Potentially Contested Visions of Sustainability.” *Environmental Science & Policy* 53, Part A:38–46. https://doi.org/10.1016/j.envsci.2015.04.012.

Chen, J., and S.-L. Shaw. 2016. "Representing the Spatial Extent of Places Based on Flickr Photos with a Representativeness-Weighted Kernel Density Estimation." *Proceedings of the 9th International Conference on Geographical Information Science*, 130–144. Montreal, QC, Canada. Springer. https://doi.org/10.1007/978-3-319-45738-3_9.

Chen, M., D. Arribas-Bel, and A. Singleton. 2020. "Quantifying the Characteristics of the Local Urban Environment Through Geotagged Flickr Photographs and Image Recognition." *ISPRS International Journal of Geo-Information* 9 (4): 264. https://doi.org/10.3390/ijgi9040264.

Cheshmehzangi, A., and T. Heat. 2012. "Urban Identities: Influences on Socio-Environmental Values and Spatial Inter-Relations." *Proceedings of the Asean Conference on Environment-Behaviour Studies (AcE-Bs)*, Bandung, Indonesia, edited by M. Y. Abbas, A. F. I. Bajunid, and N. F. N. Azhari, 253–264. Elsevier. https://doi.org/10.1016/j.sbspro.2012.03.028.

Cilliers, E. J., and W. Timmermans. 2014. "The Importance of Creative Participatory Planning in the Public Place-Making Process." *Environment & Planning B: Planning & Design* 41 (3): 413–429. https://doi.org/10.1068/b39098.

Clasper, L. T. 2018. Exploring Vernacular Perceptions of Spatial Entities: Using Twitter Data and R for Delimiting Vague, Informal Neighbourhood Units in Inner London, UK. *GI_Forum* 6 (1): 316–335. https://doi.org/10.1553/giscience2018_01_s316.

Cliff, A. D., and J. K. Ord. 1981. *Spatial Processes: Models & Applications*. London, UK: Pion.

Cooper, D. and Gregory, I. N. 2011. "Mapping the English Lake District: A Literary GIS." *Transactions of the Institute of British Geographers*, 36 (1): 89–108. https://doi.org/10.1111/j.1475-5661.2010.00405.x.

Costa, M., and L. Bonetti. 2018. "Geometrical Distortions in Geographical Cognitive Maps." *Journal of Environmental Psychology* 55:53–69. https://doi.org/10.1016/j.jenvp.2017.12.004.

Cresswell, T. 2002. "Introduction: Theorizing Place." In *Mobilizing Place, Placing Mobility*, edited by G. Verstraete and T. Cresswell, 11–31. Leiden, the Netherlands: Brill. https://doi.org/10.1163/9789004333451_003.

Cresswell, T. 2015. *Place: An Introduction*. Chichester, UK: Wiley.

Curiel, J. M., and G. A. Radvansky. 2004. "The Accuracy of Spatial Information from Temporally and Spatially Organized Mental Maps." *Psychonomic Bulletin & Review* 11 (2): 314–319. https://doi.org/10.3758/BF03196576.

Das, R. N., and J.-S. Park. 2012. "Discrepancy in Regression Estimates Between Log-Normal and Gamma: Some Case Studies." *Journal of Applied Statistics* 39 (1): 97–111. https://doi.org/10.1080/02664763.2011.578618.

Davies, C. 2020. "Places as Fuzzy Locational Categories." *Acta Psychologica* 202: 102937. https://doi.org/10.1016/j.actpsy.2019.102937.

Davis, C. P., H. M. Morrow, and G. Lupyan. 2019. "What Does a Horgous Look Like? Nonsense Words Elicit Meaningful Drawings." *Cognitive Science* 43 (10): e12791. https://doi.org/10.1111/cogs.12791.

Davis, G. A., and E. Hyun. 2005. "A Study of Kindergarten Children's Spatial Representation in a Mapping Project." *Mathematics Education Research Journal* 17 (1): 73–100. https://doi.org/10.1007/BF03217410.

de Certeau, M. 1984. "The Practice of Everyday Life." Berkeley, CA: University of California Press.

DeMiglio, L., and A. Williams. 2008. "A Sense of Place, a Sense of Well-Being." In *Sense of Place, Health and Quality of Life*, edited by J. Eyles and A. Williams, 35–50. London, UK: Routledge.

Dolma, C. 2022. "Reclaiming Place Through Marginalized Narratives – A Critical Geography and Humanistic Approach to the Cartographic Visualization of Beyoğlu, Istanbul." *Proceedings of the Third International Symposium on Platial Information Science (PLATIAL'21)*, Enschede, the Netherlands, edited by F.-B. Mocnik and R. Westerholt, 35–40. https://doi.org/10.5281/zenodo.5767184.

Donnelly, M., S. Gamsu, and S. Whewall. 2020. "Mapping the Relational Construction of People and Places." *International Journal of Social Research Methodology* 23 (1): 91–108. https://doi.org/10.1080/13645579.2019.1672284.

Doughty, K., H. Hu, and J. Smit. 2023. “Therapeutic Landscapes During the COVID-19 Pandemic: Increased and Intensified Interactions with Nature.” *Social and Cultural Geography* 24 (3–4): 661–679. https://doi.org/10.1080/14649365.2022.2052168.

Dovey, K. 2020. “Place as Assemblage.” In *The Routledge Handbook of Place*, edited by T. Edensor, A. Kalandides, and U. Kothari, 21–31. London, UK: Routledge.

Dyck, I. 2005. “Feminist Geography, the ‘Everyday’, and Local–Global Relations: Hidden Spaces of Place-Making.” *The Canadian Geographer* 49 (3): 233–243. https://doi.org/10.1111/j.0008-3658.2005.00092.x.

Ellery, P. J., and J. Ellery. 2019. “Strengthening Community Sense of Place Through Placemaking.” *Urban Planning* 4 (2): 237–248. https://doi.org/10.17645/up.v4i2.2004.

Fagerland, M. W., and D. W. Hosmer. 2012. “A Generalized Hosmer–Lemeshow Goodness-Of-Fit Test for Multinomial Logistic Regression Models.” *The Stata Journal* 12 (3): 447–453. https://doi.org/10.1177/1536867X1201200307.

Fairbairn, D. 2006. “Measuring Map Complexity.” *The Cartographic Journal* 43 (3): 224–238. https://doi.org/10.1179/000870406X169883.

Fan, J. E., D. L. K. Yamins, and N. B. Turk-Browne. 2018. “Common Object Representations for Visual Production and Recognition.” *Cognitive Science* 42 (8): 2670–2698. https://doi.org/10.1111/cogs.12676.

Feltz, C. J., and G. E. Miller. 1996. “An Asymptotic Test for the Equality of Coefficients of Variation from *K* Populations.” *Statistics in Medicine* 15 (6): 647–658. https://doi.org/10.1002/(SICI)1097-0258(19960330)15:6<647::AID-SIM184>3.0.CO;2-P.

Fox, J., and G. Monette. 1992. “Generalized Collinearity Diagnostics.” *Journal of the American Statistical Association* 87 (417): 178–183. https://doi.org/10.1080/01621459.1992.10475190.

Gagnon, J., and C. Desbiens. 2018. “Mapping Memories in a Flooded Landscape: A Place Reenactment Project in Pessamit (Quebec).” *Emotion, Space and Society* 27:39–51. https://doi.org/10.1016/j.emospa.2017.11.001.

Gao, S. 2022. “Towards Place-Based GIS.” In *New Thinking in GIScience*, edited by B. Li, X. Shi, A.-X. Zhu, C. Wang, and H. Lin, 51–58. Singapore: Springer. https://doi.org/10.1007/978-981-19-3816-0_6.

Gardony, A. L., H. A. Taylor, and T. T. Brunyé. 2016. “Gardony Map Drawing Analyzer: Software for Quantitative Analysis of Sketch Maps.” *Behavior Research Methods* 48 (1): 151–177. https://doi.org/10.3758/s13428-014-0556-x.

Getis, A. 2010. “Spatial Autocorrelation.” In *Handbook of Applied Spatial Analysis*, edited by M. M. Fischer and A. Getis, 255–278. Berlin/Heidelberg, Germany: Springer. https://doi.org/10.1007/978-3-642-03647-7_14.

Gieseking, J. J. 2013. “Where We Go from Here: The Mental Sketch Mapping Method and Its Analytic Components.” *Qualitative Inquiry* 19 (9): 712–724. https://doi.org/10.1177/1077800413500926.

Glebova, M. 2022. “Visualizing Fuzzy Boundaries of City Neighbourhoods.” *Proceedings of the Third International Symposium on Platial Information Science (PLATIAL’21)*, Enschede, the Netherlands, edited by F.-B. Mocnik and R. Westerholt, 41–47. https://doi.org/10.5281/zenodo.5767186.

Goodchild, M. F. 2015. “Space, Place and Health.” *Annals of GIS* 21 (2): 97–100. https://doi.org/10.1080/19475683.2015.1007895.

Graves, T., and L. Poraj-Wilczynska. 2009. “‘Spirit of Place’ as Process: Archaeography, Dowsing and Perceptual Mapping at Belas Knap.” *Time and Mind* 2 (2): 167–193. https://doi.org/10.2752/175169709X423673.

Greene, M. R., and D. Trivedi. 2023. “Spatial Scene Memories are Biased Towards a Fixed Amount of Semantic Information.” *Open Mind* 7:445–459. https://doi.org/10.1162/opmi_a_00088.

Grilli, L., and C. Rampichini. 2014. “Ordered Logit Model.” *Encyclopedia of Quality of Life and Well-Being Research*, edited by A. C. Michalos, 4510–4513. Dordrecht, the Netherlands: Springer. https://doi.org/10.1007/978-94-007-0753-5_2023.

Gröbe, M., and D. Burghardt. 2018. “A Contribution to the Visualization of the Diversity of Places.” *Proceedings of the 1st Workshop on Platial Analysis (PLATIAL’18)*, Heidelberg, Germany, edited by R. Westerholt, F.-B. Mocnik, and A. Zipf, 67–73. https://doi.org/10.5281/zenodo.1472751.

Halegoua, G., and E. Polson. 2021. “Exploring ‘Digital Placemaking’.” *Convergence: The International Journal of Research into New Media Technologies* 27 (3): 573–578. https://doi.org/10.1177/13548565211014828.

Hårsman Wahlström, M., K. Kourtit, and P. Nijkamp. 2020. “Planning Cities4People – a Body and Soul Analysis of Urban Neighbourhoods.” *Public Management Review* 22 (5): 687–700. https://doi.org/10.1080/14719037.2020.1718190.

Harvey, D. 1996. *Justice, Nature and the Geography of Difference*. Cambridge, MA: Wiley-Blackwell.

Hasanzadeh, K., A. Kajosaari, D. Häggman, and M. Kyttä. 2020. “A Context Sensitive Approach to Anonymizing Public Participation GIS Data: From Development to the Assessment of Anonymization Effects on Data Quality.” *Computers, Environment and Urban Systems* 83:101513. https://doi.org/10.1016/j.compenvurbsys.2020.101513.

Hasanzadeh, K., T. Laatikainen, and M. Kyttä. 2018. “A Place-Based Model of Local Activity Spaces: Individual Place Exposure and Characteristics.” *Journal of Geographical Systems* 20 (3): 227–252. https://doi.org/10.1007/s10109-017-0264-z.

Hassler, J., and V. Ceccato. 2021. “Socio-Spatial Disparities in Access to Emergency Health Care – a Scandinavian Case Study.” *PLOS ONE* 16 (12): e0261319. https://doi.org/10.1371/journal.pone.0261319.

Hátlová, K., and M. Hanus. 2020. “A Systematic Review into Factors Influencing Sketch Map Quality.” *ISPRS International Journal of Geo-Information* 9 (4): 271. https://doi.org/10.3390/ijgi9040271.

Hawthorne, T. L., K. R. Toohy, B. Yang, L. Graham, E. M. Lorenzo, H. Torres, M. McDonald, F. Rivera, K. Bouck, and L. J. Walters. 2022. “Mapping Emotional Attachment as a Measure of Sense of Place to Identify Coastal Restoration Priority Areas.” *Applied Geography* 138:102608. https://doi.org/10.1016/j.apgeog.2021.102608.

Heikinheimo, V., H. Tenkanen, T. Hiippala, and T. Toivonen. 2018. “Digital Imaginations of National Parks in Different Social Media: A Data Exploration.” *Proceedings of the 1st Workshop on Platial Analysis (PLATIAL’18)*, edited by R. Westerholt, F.-B. Mocnik, and A. Zipf, 45–52. Heidelberg, Germany.

Hobel, H., P. Fogliaroni, and A. U. Frank. 2016. “Deriving the Geographic Footprint of Cognitive Regions.” *Proceedings of the 19th AGILE Conference on Geographic Information Science*, edited by T. Sarjakoski, M. Y. Santos, and L. T. Sarjakoski, 67–84. Cham, Switzerland. Springer. https://doi.org/10.1007/978-3-319-33783-8_5.

Hollenstein, L., and R. Purves. 2010. “Exploring Place Through User-Generated Content: Using Flickr Tags to Describe City Cores.” *Journal of Spatial Information Science* 1:21–48. https://doi.org/10.5311/JOSIS.2010.1.3.

Hull, R. B., IV, M. Lam, and G. Vigo. 1994. “Place Identity: Symbols of Self in the Urban Fabric.” *Landscape and Urban Planning* 28 (2–3): 109–120. https://doi.org/10.1016/0169-2046(94)90001-9.

Ianulardo, G., and A. Stella. 2022. “Towards a Unity of Sense: A Critical Analysis of the Concept of Relation in Methodological Individualism and Holism in Economics.” *The Journal of Philosophical Economics* 15: 10013. https://doi.org/10.46298/jpe.10013.

Iosifescu Enescu, C. M., H.-R. Bär, M. Beilstein, and L. Hurni. 2020. “Place Cookies and Setting Spiders in Dream Cartography.” *Transactions in GIS* 24 (4): 944–966. https://doi.org/10.1111/tgis.12604.

Jang, K. M., and Y. Kim. 2019. “Crowd-Sourced Cognitive Mapping: A New Way of Displaying People’s Cognitive Perception of Urban Space.” *PLOS ONE* 14 (6): e0218590. https://doi.org/10.1371/journal.pone.0218590.

Jeannotte, M. S. 2015. “Cultural Mapping in Ontario: The Big Picture.” In *Cultural Mapping as Cultural Inquiry*, edited by N. Duxbury, W. F. Garrett-Petts, and D. MacLennan, 99–116. New York, NY: Routledge.

Jenkins, A., A. Croitoru, A. T. Crooks, and A. Stefanidis. 2016. “Crowdsourcing a Collective Sense of Place.” *PLOS ONE* 11 (4): e0152932. https://doi.org/10.1371/journal.pone.0152932.

Jive´n, G., and P. J. Larkham. 2003. “Sense of Place, Authenticity and Character: A Commentary.” *Journal of Urban Design* 8 (1): 67–81. https://doi.org/10.1080/1357480032000064773.

Jones, C. B., R. S. Purves, P. D. Clough, and H. Joho. 2008. “Modelling Vague Places with Knowledge from the Web.” *International Journal of Geographical Information Science* 22 (10): 1045–1065. https://doi.org/10.1080/13658810701850547.

Jones, L., R. A. Holland, J. Ball, T. Sykes, G. Taylor, L. Ingwall-King, J. L. Snaddon, and S.-H. Peh. 2020. “A Place-Based Participatory Mapping Approach for Assessing Cultural Ecosystem Services in Urban Green Space.” *People and Nature* 2 (1): 123–137. https://doi.org/10.1002/pan3.10057.

Jorgensen, B. S., and R. C. Stedman. 2001. “Sense of Place as an Attitude: Lakeshore Owners Attitudes Toward Their Properties.” *Journal of Environmental Psychology* 21 (3): 233–248. https://doi.org/10.1006/jevp.2001.0226.

Kabachnik, P. 2012. “Nomads and Mobile Places: Disentangling Place, Space and Mobility.” *Identities* 19 (2): 210–228. https://doi.org/10.1080/1070289X.2012.672855.

Kim, J., M. Vasardani, and S. Winter. 2016. “From Descriptions to Depictions: A Dynamic Sketch Map Drawing Strategy.” *Spatial Cognition and Computation* 16 (1): 29–53. https://doi.org/10.1080/13875868.2015.1084509.

Klonner, C., T. J. Usón, N. Aeschbach, and B. Höfle. 2021. “Participatory Mapping and Visualization of Local Knowledge: An Example from Eberbach, Germany.” *International Journal of Disaster Risk Science* 12 (1): 56–71. https://doi.org/10.1007/s13753-020-00312-8.

Knaps, F., S. Gottwald, C. Albert, and S. Herrmann. 2022. “Using Meaningful Places as an Indicator for Sense of Place in the Management of Social-Ecological Systems.” *Ecology and Society* 27 (4): 9. https://doi.org/10.5751/ES-13340-270409.

Kosacz, T., M. Gula, A. Poplin, T. Tobin, and F. Nourin. 2022. “Mapping Unsafe Places and Emotions: Study of Ames, Iowa.” *Proceedings of the Third International Symposium on Platial Information Science (PLATIAL’21)*, edited by F.-B. Mocnik and R. Westerholt, 5–10. Enschede, the Netherlands. https://doi.org/10.5281/zenodo.5767174.

Lafi, S. Q., and J. B. Kaneene. 1992. “An Explanation of the Use of Principal-Components Analysis to Detect and Correct for Multicollinearity.” *Preventive Veterinary Medicine* 13 (4): 261–275. https://doi.org/10.1016/0167-5877(92)90041-D.

Lawson, V., R. Purohit, F. Samuel, J. Brennan, L. Farrelly, S. M. Golden, and M. McVicar. 2022. *Public Participation in Planning in the UK: A Review of the Literature*. (Tech. Rep). Glasgow, UK: UK Collaborative Centre for Housing Evidence.

Lengen, C., and T. Kistemann. 2012. “Sense of Place and Place Identity: Review of Neuroscientific Evidence.” *Health & Place* 18 (5): 1162–1171. https://doi.org/10.1016/j.healthplace.2012.01.012.

Lewicka, M. 2011. “Place Attachment: How Far Have We Come in the Last 40 Years?” *Journal of Environmental Psychology* 31 (3): 207–230. https://doi.org/10.1016/j.jenvp.2010.10.001.

Lewicka, M., K. Rowiński, B. Iwańczak, B. Bałaj, A. M. Kula, T. Oleksy, M. Prusik, S. Toruńczyk-Ruiz, and A. Wnuk. 2019. “On the Essentialism of Places: Between Conservative and Progressive Meanings.” *Journal of Environmental Psychology* 65:101318. https://doi.org/10.1016/j.jenvp.2019.101318.

Li, L., and M. F. Goodchild. 2012. “Constructing Places from Spatial Footprints.” *Proceedings of the 1st ACM SIGSPATIAL International Workshop on Crowdsourced and Volunteered Geographic Information (GEOCROWD ‘12)*, Redondo Beach, CA, USA, edited by M. F. Goodchild, D. Pfoser, and D. Sui, 15–21. https://doi.org/10.1145/2442952.2442956.

Liu, K., P. Qiu, S. Gao, F. Lu, J. Jiang, and L. Yin. 2020. “Investigating Urban Metro Stations as Cognitive Places in Cities Using Points of Interest.” *Cities* 97:102561. https://doi.org/10.1016/j.cities.2019.102561.

Lopez, A., and A. Bosco. 2022. “Distortions in Spatial Mental Representation Affect Sketch Maps in Young Adults.” *Neurology International* 14 (4): 771–783. https://doi.org/10.3390/neurolint14040064.

Lopez, A., A. Postma, and A. Bosco. 2020. “Categorical & Coordinate Spatial Information: Can They Be Disentangled in Sketch Maps?” *Journal of Environmental Psychology* 68:101392. https://doi.org/10.1016/j.jenvp.2020.101392.

Lowet, A. S., C. Firestone, and B. J. Scholl. 2018. “Seeing Structure: Shape Skeletons Modulate Perceived Similarity.” *Attention, Perception, & Psychophysics* 80 (5): 1278–1289. https://doi.org/10.3758/s13414-017-1457-8.

Maddrell, A. 2016. “Mapping Grief. A Conceptual Framework for Understanding the Spatial Dimensions of Bereavement, Mourning and Remembrance.” *Social and Cultural Geography* 17 (2): 166–188. https://doi.org/10.1080/14649365.2015.1075579.

Malpas, J. 2018. *Place and Experience: A Philosophical Topography*. 2nd ed. Oxon, UK: Routledge.

Manivannan, C., J. Krukar, and A. Schwering. 2022. “Spatial Generalization in Sketch Maps: A Systematic Classification.” *Journal of Environmental Psychology* 83:101851. https://doi.org/10.1016/j.jenvp.2022.101851.

Marques, B., C. Freeman, L. Carter, and M. Pedersen Zari. 2020. “Sense of Place and Belonging in Developing Culturally Appropriate Therapeutic Environments: A Review.” *Societies* 10 (4): 83. https://doi.org/10.3390/soc10040083.

Massey, D. B. 2005. *For Space*. London, UK: SAGE.

Massey, D. B. 2008. “A Global Sense of Place.” In *The Cultural Geography Reader*, edited by T. Oakes and P. L. Price, 269–275. London, UK: Routledge.

McCrae, R. R. 2009. “The Five-Factor Model of Personality Traits: Consensus and Controversy.” In *The Cambridge Handbook of Personality Psychology*, edited by P. J. Corr and G. Matthews, 148–161. Cambridge, UK: Cambridge University Press. https://doi.org/10.1017/9781108264822.013.

McKenzie, G., and B. Adams. 2017. “Juxtaposing Thematic Regions Derived from Spatial and Platial User-Generated Content.” *Proceedings of the 13th International Conference on Spatial Information Theory (COSIT 2017)*, edited by E. Clementini, M. Donnelly, M. Yuan, C. Kray, P. Fogliaroni, and A. Ballatore. L’Aquila, Italy. http://dx.doi.org/10.4230/LIPIcs.COSIT.2017.20.

Miller, J. 1981. “Global Precedence in Attention and Decision.” *Journal of Experimental Psychology: Human Perception and Performance* 7 (6): 1161–1174. https://doi.org/10.1037//0096-1523.7.6.1161.

Mocnik, F.-B. 2022. “Putting Geographical Information Science in Place – Towards Theories of Platial Information and Platial Information Systems.” *Progress in Human Geography* 46 (3): 798–828. https://doi.org/10.1177/03091325221074023.

Mohsenin, M. S. 2011. *The Impact of Urban Geometry on Cognitive Maps*. Masters dissertation, Cambridge, MA: Massachusetts Institute of Technology.

Montello, D. R., A. Friedman, and D. W. Phillips. 2014. “Vague Cognitive Regions in Geography and Geographic Information Science.” *International Journal of Geographical Information Science* 28 (9): 1802–1820. https://doi.org/10.1080/13658816.2014.900178.

Montello, D. R., M. F. Goodchild, J. Gottsegen, and P. Fohl. 2003. “Where’s Downtown?: Behavioral Methods for Determining Referents of Vague Spatial Queries.” *Spatial Cognition and Computation* 3 (2–3): 185–204. https://doi.org/10.1080/13875868.2003.9683761.

Müller, S., N. Backhaus, and M. Buchecker. 2020. “Mapping Meaningful Places: A Tool for Participatory Siting of Wind Turbines in Switzerland?” *Energy Research & Social Science* 69:101573. https://doi.org/10.1016/j.erss.2020.101573.

Næss, P. 2016. “Urban Planning: Residential Location and Compensatory Behaviour in Three Scandinavian Cities.“ In *Rethinking Climate and Energy Policies*, edited by T. Santarius, H. J. Walnum, and C. Aall, 181–207. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-319-38807-6_11.

Nagelkerke, N. J. D. 1991. “A Note on a General Definition of the Coefficient of Determination.” *Biometrika* 78 (3): 691–692. https://doi.org/10.1093/biomet/78.3.691.

Nanda, G., and A. Khare. 2018. “Spatial Mapping of ‘People–Place ties’ as an Integral Part of Heritage Management Process.” *Journal of Heritage Management* 3 (2): 192–208. https://doi.org/10.1177/2455929618807984.

de Nardi, S. 2014. “Senses of Place, Senses of the Past: Making Experiential Maps as Part of Community Heritage Fieldwork.” *Journal of Community Archaeology & Heritage* 1 (1): 5–22. https://doi.org/10.1179/2051819613Z.0000000001.

Navon, D. 1977. “Forest Before Trees: The Precedence of Global Features in Visual Perception.” *Cognitive Psychology* 9 (3): 353–383. https://doi.org/10.1016/0010-0285(77)90012-3.

Nelson, J., J. J. Ahn, and E. A. Corley. 2020. “Sense of Place: Trends from the Literature.” *Journal of Urbanism: International Research on Placemaking and Urban Sustainability* 13 (2): 236–261. https://doi.org/10.1080/17549175.2020.1726799.

Nummi, P. 2018. “Crowdsourcing Local Knowledge with PPGIS and Social Media for Urban Planning to Reveal Intangible Cultural Heritage.” *Urban Planning* 3 (1): 100–115. https://doi.org/10.17645/up.v3i1.1266.

Olwig, K. R. 2006. “Place Contra Space in a Morally Just Landscape.” *Norsk Geografisk Tidsskrift – Norwegian Journal of Geography* 60 (1): 24–31. https://doi.org/10.1080/00291950500537216 .

Pánek, J., M. R. Glass, and L. Marek. 2020. “Evaluating a Gentrifying Neighborhood’s Changing Sense of Place Using Participatory Mapping.” *Cities* 102:102723. https://doi.org/10.1016/j.cities.2020.102723.

Parks-Leduc, L., G. Feldman, and A. Bardi. 2015. “Personality Traits and Personal Values: A Meta-Analysis.” *Personality and Social Psychology Review* 19 (1): 3–29. https://doi.org/10.1177/1088868314538548.

Pászto, V., A. Brychtová, and L. Marek. 2015. “On Shape Metrics in Cartographic Generalization: A Case Study of the Building Footprint Geometry.” In *Modern Trends in Cartography: Selected Papers of Cartocon 2014*, edited by J. Brus, A. Vondrakova, and V. Vozenilek, 397–407. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-319-07926-4_30.

Peng, J., D. Strijker, and Q. Wu. 2020. “Place Identity: How Far Have We Come in Exploring Its Meanings?” *Frontiers in Psychology* 11:294. https://doi.org/10.3389/fpsyg.2020.00294.

Phillips, D. W., and D. R. Montello. 2017. “Defining the Community of Interest as Thematic and Cognitive Regions.” *Political Geography* 61:31–45. https://doi.org/10.1016/j.polgeo.2017.06.005.

Poorthuis, A. 2018. “How to Draw a Neighborhood? The Potential of Big Data, Regionalization, and Community Detection for Understanding the Heterogeneous Nature of Urban Neighborhoods.” *Geographical Analysis* 50 (2): 182–203. https://doi.org/10.1111/gean.12143.

Pordata. 2021a. “População residente segundo os Censos: total e por sexo.” Accessed September 1, 2023. https://www.pordata.pt/municipios/populacao+residente+segundo+os+censos+total+e+por+sexo-17.

Pordata. 2021b. “População residente: total e por grandes grupos etários.” Accessed September 1, 2023. https://www.pordata.pt/municipios/populacao+residente+total+e+por+grandes+grupos+etarios-390.

Potter, A. E. 2015. “The Commons as a Tourist Commodity: Mapping Memories and Changing Sense of Place on the Island of Barbuda.” In *Social Memory and Heritage Tourism Methodologies*, edited by S. P. Hanna, A. E. Potter, E. A. Modlin, P. Carter, and D. L. Butler, 109–128. London, UK: Routledge.

Povilaitienė, I. 2021. *Assessment and Modelling of the Identity of Cityscape*. Doctoral dissertation, Kaunas, Lithuania: Kauno Technologijos Universitetas.

Powell, K. A. 2008. “ReMapping the City: Palimpsest, Place, and Identity in Art Education Research.” *Studies in Art Education* 50 (1): 6–21. https://doi.org/10.1080/00393541.2008.11518752.

Proudfoot, J. 2019. “Traumatic Landscapes: Two Geographies of Addiction.” *Social Science & Medicine* 228:194–201. https://doi.org/10.1016/j.socscimed.2019.03.020.

Purves, R. S., S. Winter, and W. Kuhn. 2019. “Places in Information Science.” *Journal of the Association for Information Science and Technology* 70 (11): 1173–1182.

Qazimi, S. 2014. “Sense of Place and Place Identity.” *European Journal of Social Science Education and Research* 1 (1): 248–252.

Raymond, C. M., M. Kyttä, and R. Stedman. 2017. “Sense of Place, Fast and Slow: The Potential Contributions of Affordance Theory to Sense of Place.” *Frontiers in Psychology* 8:1674. https://doi.org/10.3389/fpsyg.2017.01674.

Relph, E. 1976. *Place and Placelessness*. London, UK: Pion.

Rezvani, Z., A. Katanforoush, and H. Pouretemad. 2020. “Global Precedence Changes by Environment: A Systematic Review and Meta-Analysis on Effect of Perceptual Field Variables on Global-Local Visual Processing.” *Attention, Perception, & Psychophysics* 82 (5): 2348–2359. https://doi.org/10.3758/s13414-020-01997-1.

Russell, J. A., and G. Pratt. 1980. “A Description of the Affective Quality Attributed to Environments.” *Journal of Personality & Social Psychology* 38 (2): 311–322. https://doi.org/10.1037/0022-3514.38.2.311.

Rust, J., and S. Golombok. 2014. *Modern Psychometrics: The Science of Psychological Assessment*. London, UK: Routledge.

Sablé-Meyer, M., K. Ellis, J. Tenenbaum, and S. Dehaene. 2022. “A Language of Thought for the Mental Representation of Geometric Shapes.” *Cognitive Psychology* 139:101527. https://doi.org/10.1016/j.cogpsych.2022.101527.

Sablé-Meyer, M., J. Fagot, S. Caparos, T. van Kerkoerle, M. Amalric, and S. Dehaene. 2021. “Sensitivity to Geometric Shape Regularity in Humans and Baboons: A Putative Signature of Human Singularity.” *Proceedings of the National Academy of Sciences* 118 (16): e2023123118. https://doi.org/10.1073/pnas.2023123118.

Salah Ouf, A. M. 2001. “Authenticity and the Sense of Place in Urban Design.” *Journal of Urban Design* 6 (1): 73–86. https://doi.org/10.1080/13574800120032914.

Santana, P., and H. Nogueira. 2008. “Environment and Health: Place, Sense of Place and Weight Gain in Urban Areas.” In *Sense of Place, Health and Quality of Life*, edited by J. Eyles and A. Williams, 173–188. London, UK: Routledge.

Savić, J. 2017. “Sense(s) of the City: Cultural Mapping in Porto, Portugal.” *City, Culture and Society* 11:12–19. https://doi.org/10.1016/j.ccs.2017.08.001.

Schlieder, C., and C. Matyas. 2009. “Photographing a City: An Analysis of Place Concepts Based on Spatial Choices.” *Spatial Cognition and Computation* 9 (3): 212–228. https://doi.org/10.1080/13875860903121848.

Schwering, A., J. Krukar, C. Manivannan, M. Chipofya, and S. Jan. 2022. “Generalized, Inaccurate, Incomplete: How to Comprehensively Analyze Sketch Maps Beyond Their Metric Correctness.” *Proceedings of the 15th International Conference on Spatial Information Theory (COSIT 2022)*, Kobe, Japan. https://doi.org/10.4230/LIPIcs.COSIT.2022.8.

Schwering, A., J. Wang, M. Chipofya, S. Jan, R. Li, and K. Broelemann. 2014. “SketchMapia: Qualitative Representations for the Alignment of Sketch and Metric Maps.” *Spatial Cognition and Computation* 14 (3): 220–254. https://doi.org/10.1080/13875868.2014.917378.

Seamon, D. 2018. *Life Takes Place: Phenomenology, Lifeworlds, and Place Making*. New York, NY, USA: Routledge.

Seamon, D., and T. Larsen. 2020. “Humanistic Geography.” In *International Encyclopedia of Geography*, edited by D. Richardson, N. Castree, M. F. Goodchild, A. Kobayashi, W. Liu, and R. A. Marston. Hoboken, NJ, USA: Wiley.

Seamon, D., and A. Lundberg. 2017. “Humanistic Geography.” In *International Encyclopedia of Geography*, edited by D. Richardson, N. Castree, M. F. Goodchild, A. Kobayashi, W. Liu, and R. A. Marston. Hoboken, NJ, USA: Wiley.

Seamon, D., and C. Nordin. 1980. “Marketplace as Place Ballet: A Swedish Example.” *Landscape* 24:35–41.

Shamai, S., and Z. Ilatov. 2005. “Measuring Sense of Place: Methodological Aspects.” *Tijdschrift voor economische en sociale geografie* 96 (5): 467–476. https://doi.org/10.1111/j.1467-9663.2005.00479.x.

Shannon, C. E. 1948. “A Mathematical Theory of Communication.” *Bell System Technical Journal* 27 (3): 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x.

Smirnov, O. A. 2016. “Geographic Space: An Ancient Story Retold.” *Transactions of the Institute of British Geographers* 41 (4): 585–596. https://doi.org/10.1111/tran.12127.

Smith, B. 2019. “Drawing Boundaries.” In The *Philosophy of GIS*, edited by T. Tambassi, 137–158. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-030-16829-2_7.

Soini, K. 2001. “Exploring Human Dimensions of Multifunctional Landscapes Through Mapping and Map-Making.” *Landscape and Urban Planning* 57 (3–4): 225–239. https://doi.org/10.1016/S0169-2046(01)00206-7.

Spenger, D., S. Kordel, and T. Weidinger. 2023. “Mapping Places of Encounter: An Integrative Methodological Approach to Understanding Social Inclusion.” *International Journal of Qualitative Methods* 22:1–12. https://doi.org/10.1177/16094069231151304.

Steiger, E., R. Westerholt, B. Resch, and A. Zipf. 2015. “Twitter as an Indicator for Whereabouts of People? Correlating Twitter with UK Census Data.” *Computers, Environment and Urban Systems* 54:255–265. https://doi.org/10.1016/j.compenvurbsys.2015.09.007.

Steiner, E., Z. Frank, I. Gregory, D. Bodenhamer, and I. Ezeani. 2023. “Spatio-Textual Regions: Extracting Sense of Place from Spatial Narratives.” *Proceedings of the Fourth International Symposium on Platial Information Science (PLATIAL’23)*, edited by R. Westerholt and F.-B. Mocnik, 15–22. Dortmund, Germany. https://doi.org/10.5281/zenodo.8286257.

Sun, Z., and C. Firestone. 2021. “Curious Objects: How Visual Complexity Guides Attention and Engagement.” *Cognitive Science* 45 (4): e12933. https://doi.org/10.1111/cogs.12933.

Sun, Z., and C. Firestone. 2022a. “Beautiful on the Inside: Aesthetic Preferences and the Skeletal Complexity of Shapes.” *Perception* 51 (12): 904–918. https://doi.org/10.1177/03010066221124872.

Sun, Z., and C. Firestone. 2022b. “Seeing and Speaking: How Verbal “Description Length” Encodes Visual Complexity.” *Journal of Experimental Psychology: General* 151 (1): 82–96. https://doi.org/10.1037/xge0001076.

Tan, S.-K., S.-H. Tan, Y.-S. Kok, and S.-W. Choon. 2018. “Sense of Place and Sustainability of Intangible Cultural Heritage – the Case of George Town and Melaka.” *Tourism Management* 67:376–387. https://doi.org/10.1016/j.tourman.2018.02.012.

Tang, M., Z. Falomir, C. Freksa, Y. Sheng, and H. Lyu. 2020. “Extracting Invariant Characteristics of Sketch Maps: Towards Place Query-By-Sketch.” *Transactions in GIS* 24 (4): 903–943. https://doi.org/10.1111/tgis.12621.

Thrift, N. 2008. *Non-Representational Theory: Space, Politics, Affect*. Oxon, UK: Routledge.

Thrift, N. 2009. “Space: The Fundamental Stuff of Geography.” In *Key Concepts in Geography*, edited by N. Clifford, S. Holloway, S. P. Rice, and G. Valentine, 85–96. 2nd ed. London, UK: SAGE.

Tomalin, E., J. Sadgrove, and R. Summers. 2019. “Health, Faith and Therapeutic Landscapes: Places of Worship as Black, Asian and Minority Ethnic (BAME) Public Health Settings in the United Kingdom.” *Social Science & Medicine* 230:57–65. https://doi.org/10.1016/j.socscimed.2019.03.006.

Touya, G., and A. W. Reimer. 2015. “Inferring the Scale of OpenStreetMap Features.” In *OpenStreetMap in GIScience: Experiences, Research, and Applications*, edited by J. J. Arsanjani, A. Zipf, P. Mooney, and M. Helbich, 81–99. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-319-14280-7_5.

Tuan, Y.-F. 1977. *Space and Place: The Perspective of Experience*. Minneapolis, MN, USA: University of Minnesota Press.

Tuan, Y.-F. 2006. “Humanistic Geography – a Personal View.” *Progress in Geography* 25 (2): 1–7. https://doi.org/10.11820/dlkxjz.2006.02.001.

Twaroch, F. A., P. Brindley, P. D. Clough, C. B. Jones, R. C. Pasley, and S. Mansbridge. 2019. “Investigating Behavioural and Computational Approaches for Defining Imprecise Regions.” *Spatial Cognition and Computation* 19 (2): 146–171. https://doi.org/10.1080/13875868.2018.1531871.

Verbrugge, L., M. Buchecker, X. Garcia, S. Gottwald, S. Müller, S. Præstholm, and A. Stahl Olafsson. 2019. “Integrating Sense of Place in Planning and Management of Multifunctional River Landscapes: Experiences from Five European Case Studies.” *Sustainability Science* 14 (3): 669–680. https://doi.org/10.1007/s11625-019-00686-9.

Wang, J., C. Mülligann, and A. Schwering. 2011. “An Empirical Study on Relevant Aspects for Sketch Map Alignment.” *Proceedings of the 14th AGILE Conference on Geographic Information Science*, edited by S. Geertman, W. Reinhardt, and F. Toppen, 497–518. Berlin/Heidelberg, Germany. Springer. https://doi.org/10.1007/978-3-642-19789-5_25.

Wang, J., and A. Schwering. 2009. “The Accuracy of Sketched Spatial Relations: How Cognitive Errors Affect Sketch Representation.” *International Workshop on Presenting Spatial Information: Granularity, Relevance, and Integration at the 9th Conference on Spatial Information Theory (COSIT)*, edited by K. Stewart, C. Claramunt, M. Denis, and G. Ligozat, 40–47. Aber Wrac’h, France.

Wang, J., and A. Schwering. 2015. “Invariant Spatial Information in Sketch Maps—A Study of Survey Sketch Maps of Urban Areas.” *Journal of Spatial Information Science* 11:31–52. http://dx.doi.org/10.5311/JOSIS.2015.11.225.

Wang, J., and M. Worboys. 2017. “Ontologies and Representation Spaces for Sketch Map Interpretation.” *International Journal of Geographical Information Science* 31 (9): 1697–1721. https://doi.org/10.1080/13658816.2017.1309043.

Wartmann, F. M., E. Acheson, and R. S. Purves. 2018. “Describing and Comparing Landscapes Using Tags, Texts, and Free Lists: An Interdisciplinary Approach.” *International Journal of Geographical Information Science* 32 (8): 1572–1592. https://doi.org/10.1080/13658816.2018.1445257.

Westerholt, R. 2019. “Methodological Aspects of the Spatial Analysis of Geosocial Media Feeds: From Locations Towards Places.” *gis Science: Die Zeitschrift für Geoinformatik* 31 (31): 65–76.

Westerholt, R. 2022. “Exploratory Statistical Analysis of Spatial Structures in Urban Datasets.” In *Metropolitan Research: Methods and Approaches*, edited by J. Gurr, R. Parr, and D. Hardt, 37–61. Bielefeld, Germany: transcript. http://dx.doi.org/10.14361/9783839463109-003.

Westerholt, R., A. Acedo, and M. Naranjo-Zolotov. 2022. “Exploring Sense of Place in Relation to Urban Facilities – Evidence from Lisbon.” *Cities* 127:103750. https://doi.org/10.1016/j.cities.2022.103750.

Westerholt, R., M. Gröbe, A. Zipf, and D. Burghardt. 2018. “Towards the Statistical Analysis and Visualization of Places.” *Proceedings of the 10th International Conference on Geographic Information Science (GIScience 2018)*, edited by S. Winter, M. Sester, and A. L. Griffin. Melbourne, VIC, Australia. http://dx.doi.org/10.4230/LIPIcs.GIScience.2018.63.

Westerholt, R., F.-B. Mocnik, and A. Comber. 2020. “A Place for Place: Modelling and Analysing Platial Representations.” *Transactions in GIS* 24 (4): 811–818. https://doi.org/10.1111/tgis.12647.

Wiens, B. L. 1999. “When Log-Normal and Gamma Models Give Different Results: A Case Study.” *American Statistician* 53 (2): 89–93. https://doi.org/10.1080/00031305.1999.10474437.

Wilder, J., J. Feldman, and M. Singh. 2016. “The Role of Shape Complexity in the Detection of Closed Contours.” *Vision Research* 126:220–231. https://doi.org/10.1016/j.visres.2015.10.011.

Williams, A. 2017. *Therapeutic Landscapes*. London, UK: Routledge.

Winter, S., and C. Freksa. 2012. “Approaching the Notion of Place by Contrast.” *Journal of Spatial Information Science* 5 (5): 31–50. https://doi.org/10.5311/JOSIS.2012.5.90.

Woodcock, I., S. Wollan, and K. Dovey. 2015. “Would You Like a Code with That? Place-Based Planning and Mapping Neighbourhood Fields of Care.” In *Instruments of Planning*, edited by R. Leshinsky and C. Legacy, 125–141. New York, NY: Routledge.

Woods, M., F. Fois, J. Heley, L. Jones, A. Onyeahialam, S. Saville, and M. Welsh. 2021. “Assemblage, Place and Globalisation.” *Transactions of the Institute of British Geographers* 46 (2): 284–298. https://doi.org/10.1111/tran.12430.

Wu, X., J. Wang, L. Shi, Y. Gao, and Y. Liu. 2019. “A Fuzzy Formal Concept Analysis-Based Approach to Uncovering Spatial Hierarchies Among Vague Places Extracted from User-Generated Data.” *International Journal of Geographical Information Science* 33 (5): 991–1016. https://doi.org/10.1080/13658816.2019.1566550.

Yang, T., and B. Hillier. 2007. “The Fuzzy Boundary: The Spatial Definition of Urban Areas.” *Proceedings of the 6th International Space Syntax Symposium*, Istanbul, Turkey, 91. Istanbul, Turkey.

Zare Zardiny, A., and F. Hakimpour. 2021. “Integration of Sketch Maps in Community Mapping Activities.” *Spatial Cognition and Computation* 21 (2): 114–142. https://doi.org/10.1080/13875868.2020.1841202.

Zelianskaia, N. L., K. I. Belousov, T. N. Galinskaia, and D. A. Ichkineeva. 2020. “Naive Geography: Geoconceptology and Topology of Geomental Maps.” *Heliyon* 6 (12): e05644. https://doi.org/10.1016/j.heliyon.2020.e05644.

Zhang, C., M. Tang, and Y. Sheng. 2024. “Spatial Relationship Analysis of Geographic Elements in Sketch Maps at the Meso and Micro Spatial Scales.” *ISPRS International Journal of Geo-Information* 13 (1): 32. https://doi.org/10.3390/ijgi13010032.

Zhu, Y. 2023. “A Review of Complexity Metrics for Data Visualization.” *Proceedings of the 27th International Conference on Information Visualisation (IV)*, 131–135. Tampere, Finland. IEEE. https://doi.org/10.1109/IV60283.2023.00031.

Appendix A. Invitation letter introducing the survey

Original Portuguese version

Caro Cidadão,

A fase de Apresentação de Propostas ao Orçamento Participativo de Lisboa 2017 já terminou. Entre 18 de abril e 11 de junho percorremos todas as zonas da cidade, promovendo cidadania ativa, através da realização de Sessões Participativas e participando em vários eventos e iniciativas de rua.

Nesta edição em que o OP lisboa celebra 10 anos, o balanço desta 1ª fase é positivo, facilitar a participação e o envolvimento dos cidadãos na governação da cidade, dando oportunidade de contribuir para uma cidade melhor para todos, foi um objectivo alcançado.

Foram muitos os cidadãos que responderam ao nosso apelo, apresentando as suas propostas para Lisboa, que serão apreciadas internamente pelos serviços municipais competentes, entre 19 de junho e 24 de Setembro, dando cumprimento à segunda fase do OP – Análise das Propostas.

Aproveitamos este contacto para vos convidar a participar no inquérito sobre o 'Sentido do local, capital social e participação cidadã'. O Município de Lisboa tem vindo a reforçar os mecanismos de participação junto dos cidadãos com o objetivo de se prenunciarem sobre a cidade, nas suas várias áreas de competência, envolvendo-os nas dinâmicas de governação da cidade, através dos processos participativos.

Com o objectivo de perceber de que modo os locais e as relações sociais do cidadão influenciam a sua participação na cidade, a CMLisboa disponibilizou-se para colaborar num projeto de investigação da Nova Information Management School (NOVA IMS) da Universidade Nova de Lisboa, que aborda esta temática.

Nesse sentido, solicitamos a sua disponibilidade e colaboração para responder ao inquérito através do seguinte link: http://placeandcity.com

Por favor, responda ao inquérito num computador portátil ou num computador de secretária, dado que algumas funções não funcionam bem em telemóveis e outros dispositivos semelhantes.

Às submissões nº 10, nº 50, nº 100, nº 200, nº 500 e nº 1000, será atribuído um cartão oferta no montante de 50,00€. Para se habilitar a esta oferta, tem de fornecer o seu email no campo indicado no final do inquérito. Caso os números da oferta não estejam identificados, a oferta será entregue ao número imediatamente a seguir, devidamente identificado com o respetivo email.

Obrigado pela sua participação!

Translated English version

Dear Citizen,

The phase for submitting proposals to the Lisbon Participatory Budget 2017 is now over. Between 18 April and 11 June we toured all areas of the city, promoting active citizenship by holding Participatory Sessions and taking part in various street events and initiatives.

In this edition, in which the Lisbon Participatory Budget celebrates its 10th anniversary, the balance of this first phase is positive: facilitating the participation and involvement of citizens in the governance of the city, giving them the opportunity to contribute to a better city for all, was an objective that was achieved.

Many citizens responded to our call, submitting their proposals for Lisbon, which will be assessed internally by the relevant municipal services between 19 June and 24 September, leading to the second phase of the Participatory Budget – Analysis of Proposals.

We would like to take this opportunity to invite you to take part in the survey on 'Sense of place, social capital and citizen participation'. The Municipality of Lisbon has been reinforcing mechanisms for citizen participation with the aim of giving citizens a say in the city, in its various areas of competence, involving them in the dynamics of city governance through participatory processes.

With the aim of understanding how citizens' locations and social relationships influence their participation in the city, CMLisboa has offered to collaborate on a research project at the Nova Information Management School (NOVA IMS) of the Universidade Nova de Lisboa, which addresses this issue.

We therefore ask for your availability and co-operation in answering the survey via the following link: http://placeandcity.com

Please answer the survey on a laptop or desktop computer, as some functions do not work well on mobile phones and other similar devices.

Submissions no. 10, no. 50, no. 100, no. 200, no. 500 and no. 1000 will be awarded a gift voucher worth €50.00. To qualify for this offer, you must provide your email address in the field at the end of the survey. If the offer numbers are not identified, the offer will be given to the immediately following number, duly identified with their email address.

Thank you for your participation!

Appendix B. Statements used to operationalise control variables

Table B1. The queried statements used to operationalise the accompanying control variables sociability, usability, aesthetic impression, and accessibility. Each statement was rated by the respondents in terms of Likert items ranging from 1 (strongly disagree) to 5 (strongly agree).

Variable	Label	Statement
Sociability	so	Sociability (neighbourly, friendly, interactive, welcoming, etc.)
Usability	us	Uses & activities (fun, active, vital, useful, etc.)
Aesthetic impression	ae	Comfort & image (clean, green, spiritual, attractive, etc.)
Accessiblity	ac	Access & linkage (continuity, walkable, accessible, proximity, etc.)

The statements above have been translated and were presented to the Lisbon-based participants in Portuguese. The identifiers so, us, ae, and ac are used as variable names in Section 4.2. Please note that the labels in the second column are brief summaries for use in this article. They were not presented to the respondents in the survey.

Appendix C. Approximation of tangent angles

The angles involved in the statistical considerations in Section 3.2 are not those included between two consecutive line segments, but those measured between the turning segments and the tangents of idealised, hypothetical smooth contours at the turning points. Since these tangents are not defined for the sharp corners of polygons due to their non-differentiability, we must approximate the corresponding angles with an adequate approach that represents the assumed smooth contours locally. The way we approximate the required tangents in this work is through the circumcircles of the triangles formed by two respective line segments when closed and Figure C1 illustrates our approach. The first step is to determine the coordinates of the circumcentres of the circumcircles. The circumcentres are the points at which the centred lines perpendicular to the sides of the triangle intersect. Let x_A, x_B, x_C and y_A, y_B, y_C be the coordinates of the start and end points of the line segments involved. The coordinates x_U, y_U of the circumcentres are given as

$$x_U = \frac{(x_A^2 + y_A^2)(y_B - y_C) + (x_B^2 + y_B^2)(y_C - y_A) + (x_C^2 + y_C^2)(y_A - y_B)}{d},$$

$$y_U = \frac{(x_A^2 + y_A^2)(x_C - x_B) + (x_B^2 + y_B^2)(x_C - x_A) + (x_C^2 + y_C^2)(x_A - x_B)}{d},$$

with $d = 2(x_A(y_B - y_C) + x_B(y_C - y_A) + x_C(y_A - y_B))$. The circumcircle radii are then given by the distances between the centres of the circles to one of the three corresponding points of the triangles, as these points are guaranteed to lie on the circumcircles. In the next step, we need to calculate the linear equations of the tangents at the respective points B, i.e. at the turning points we are interested in. For each circumcircle, we can determine the gradient of a line segment that connects U and B. This is given as $m_{\overline{UB}} = \frac{\delta_y}{\delta_x}$ and helps us to calculate the slope of the tangent, as the tangent is perpendicular to the line $\overline{UB}$. The latter implies that the slope of the tangent T is given as

$$m_T = -\frac{1}{m_{\overline{UB}}}.$$

With this and the slope $m_{\overline{BC}}$ of the line string connecting points B and C we can calculate the acute angle α enclosed in-between the tangent line and the continuing line segment, which is given by

$$\alpha = \arctan\left(\frac{m_{\overline{BC}} - m_T}{1 + m_{\overline{BC}} \cdot m_T}\right).$$

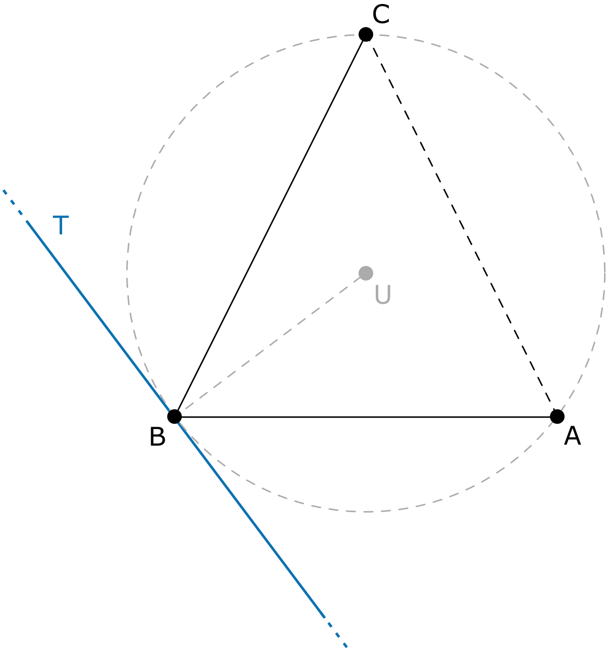


Figure C1. Illustration of the tangent approximation at turning points. A, B and C denote the start and end points of the line segments involved (all shown in black). U is the circumcentre, which serves as the centre point of the circle that runs through all three points of the line segments. All auxiliary calculated constructs are shown in grey. The tangent T is shown as a solid blue line.

Appendix D. Baseline-category logit modelling results

Table D1. Results of the baseline-category logit modelling for PA1 (Easing). The prefixes 1 to 5 correspond to the respective Likert levels of the variable.

IV	β_p	SE	$\hat{p}$	IV	β_p	SE	$\hat{p}$
1~Intercept	-26.66	2528.08	0.99	4~ae.L	0.30	1.60	0.85
2~Intercept	-25.50	4000.13	0.99	5~ae.L	0.45	1.68	0.79
4~Intercept	1.48	1.91	0.44	1~ae.Q	10.55	12734.85	1.00
5~Intercept	0.29	2.08	0.89	2~ae.Q	0.93	15488.16	1.00
1~so.L	-21.00	9649.77	1.00	4~ae.Q	1.89	1.45	0.19
2~so.L	18.51	7607.78	1.00	5~ae.Q	2.90	1.54	0.06^{*}
4~so.L	2.81	1.41	0.05^{**}	1~ae.C	-5.84	6050.30	1.00
5~so.L	2.91	1.47	0.05^{**}	2~ae.C	7.33	9052.96	1.00
1~so.Q	13.18	8084.69	1.00	4~ae.C	0.63	0.93	0.50
2~so.Q	-5.52	6190.27	1.00	5~ae.C	0.18	1.01	0.86
4~so.Q	-0.94	1.18	0.43	1~ae.4	2.43	7146.78	1.00
5~so.Q	0.03	1.22	0.98	2~ae.4	-14.39	5091.56	1.00
1~so.C	0.17	5118.67	1.00	4~ae.4	0.14	0.56	0.80
2~so.C	22.50	4721.28	1.00	5~ae.4	0.18	0.63	0.78
4~so.C	0.22	0.82	0.79	1~ac.L	-14.24	8109.67	1.00
5~so.C	-0.10	0.92	0.91	2~ac.L	11.70	17008.79	1.00
1~so.4	-6.50	5771.60	1.00	4~ac.L	0.07	1.50	0.96
2~so.4	-8.70	3621.21	1.00	5~ac.L	1.82	1.74	0.30
4~so.4	-0.64	0.54	0.23	1~ac.Q	9.25	13654.44	1.00
5~so.4	-0.54	0.63	0.39	2~ac.Q	-8.80	14375.05	1.00
1~us.L	16.79	15912.54	1.00	4~ac.Q	2.17	1.27	0.09^{*}
2~us.L	-16.80	2605.55	0.99	5~ac.Q	0.99	1.46	0.50
4~us.L	0.57	1.19	0.64	1~ac.C	5.53	4824.08	1.00
5~us.L	0.49	1.19	0.68	2~ac.C	5.20	8504.40	1.00
1~us.Q	-13.92	14729.11	1.00	4~ac.C	-0.87	0.89	0.33
2~us.Q	23.89	3501.43	0.99	5~ac.C	0.46	1.00	0.64
4~us.Q	-0.33	0.99	0.74	1~ac.4	-9.16	15252.64	1.00
5~us.Q	0.63	0.99	0.52	2~ac.4	-1.23	3214.36	1.00
1~us.C	11.39	9362.76	1.00	4~ac.4	0.51	0.59	0.39
2~us.C	5.37	2813.54	1.00	5~ac.4	-0.25	0.66	0.71
4~us.C	0.32	0.75	0.67	1~pca1	0.58	1.62	0.72
5~us.C	0.22	0.81	0.79	2~pca1	-0.40	1.04	0.70
1~us.4	-7.40	15595.33	1.00	4~pca1	0.13	0.16	0.44
2~us.4	-1.35	4160.92	1.00	5~pca1	0.12	0.18	0.51
4~us.4	0.16	0.54	0.77	1~pca2	-2.24	10.02	0.82
5~us.4	0.20	0.63	0.75	2~pca2	0.60	3.56	0.87
1~ae.L	-10.16	5562.13	1.00	4~pca2	0.40	1.03	0.70
2~ae.L	11.76	18105.92	1.00	5~pca2	-0.11	1.11	0.92

(a) PA1: Easing (b) PA1 (continued)

Hosmer–Lemeshow: $\chi^2_{32} \geq 100, p \leq 0.01$
Nagelkerke $R^2 = 0.55$

Table D2. Results of the baseline-category logit modelling for PA2 (Joy). The prefixes 1 to 5 correspond to the respective Likert levels of the variable.

IV	β_p	SE	$\hat{p}$	IV	β_p	SE	$\hat{p}$
1∼Intercept	-26.98	2538.27	0.99	4∼ae.L	0.45	1.30	0.73
2∼Intercept	-40.53	4591.36	0.99	5∼ae.L	-0.24	1.34	0.86
4∼Intercept	-1.95	3083.05	1.00	1∼ae.Q	10.55	13240.42	1.00
5∼Intercept	2.62	1.77	0.14	2∼ae.Q	-16.67	6129.16	1.00
1∼so.L	-22.59	10128.80	1.00	4∼ae.Q	2.19	1.10	0.05^{**}
2∼so.L	6.07	7589.25	1.00	5∼ae.Q	3.38	1.16	$\leq 0.01^{***}$
4∼so.L	13.06	9749.47	1.00	1∼ae.C	-6.88	6213.71	1.00
5∼so.L	0.70	1.03	0.49	2∼ae.C	-0.82	3626.06	1.00
1∼so.Q	13.82	8482.66	1.00	4∼ae.C	-0.74	0.75	0.32
2∼so.Q	-6.67	6414.08	1.00	5∼ae.C	-0.36	0.79	0.65
4∼so.Q	-9.98	8239.80	1.00	1∼ae.4	2.44	7418.16	1.00
5∼so.Q	1.05	0.85	0.22	2∼ae.4	-3.48	1370.52	1.00
1∼so.C	-0.48	5380.58	1.00	4∼ae.4	0.05	0.48	0.92
2∼so.C	5.96	3794.62	1.00	5∼ae.4	-0.21	0.56	0.71
4∼so.C	5.62	4874.73	1.00	1∼ac.L	-13.39	8290.16	1.00
5∼so.C	-0.51	0.71	0.47	2∼ac.L	3.82	6606.48	1.00
1∼so.4	-6.51	6334.35	1.00	4∼ac.L	1.61	0.97	0.10^{*}
2∼so.4	-1.14	1434.23	1.00	5∼ac.L	2.50	1.27	0.05^{**}
4∼so.4	-2.89	1842.48	1.00	1∼ac.Q	7.60	14983.42	1.00
5∼so.4	-0.30	0.57	0.60	2∼ac.Q	-12.37	5583.49	1.00
1∼us.L	16.80	16493.84	1.00	4∼ac.Q	-0.63	0.85	0.46
2∼us.L	0.07	6413.57	1.00	5∼ac.Q	-0.84	1.08	0.44
4∼us.L	0.68	1.02	0.50	1∼ac.C	6.22	4882.73	1.00
5∼us.L	0.59	1.06	0.58	2∼ac.C	-12.16	5541.30	1.00
1∼us.Q	-13.60	16367.59	1.00	4∼ac.C	0.64	0.66	0.33
2∼us.Q	-16.08	5420.45	1.00	5∼ac.C	0.79	0.79	0.32
4∼us.Q	-0.22	0.85	0.80	1∼ac.4	-9.43	17036.68	1.00
5∼us.Q	0.99	0.91	0.28	2∼ac.4	4.14	3665.45	1.00
1∼us.C	11.41	9955.42	1.00	4∼ac.4	-0.27	0.51	0.59
2∼us.C	-2.16	3206.78	1.00	5∼ac.4	0.17	0.60	0.78
4∼us.C	0.06	0.69	0.93	1∼pca1	0.63	1.62	0.70
5∼us.C	0.19	0.74	0.80	2∼pca1	0.21	0.43	0.63
1∼us.4	-8.12	17672.39	1.00	4∼pca1	0.20	0.14	0.16
2∼us.4	-4.00	1212.05	1.00	5∼pca1	0.18	0.17	0.30
4∼us.4	0.22	0.52	0.68	1∼pca2	-1.84	9.96	0.85
5∼us.4	-0.60	0.67	0.37	2∼pca2	-7.23	4.83	0.13
1∼ae.L	-10.64	5667.64	1.00	4∼pca2	1.27	0.91	0.16
2∼ae.L	0.41	7252.12	1.00	5∼pca2	1.75	0.98	0.07^{*}

(a) PA2: Joy (b) PA2 (continued)

Hosmer–Lemeshow: $\chi^2_{32} \geq 100, p \leq 0.01$
Nagelkerke $R^2 = 0.53$

Table D3. Results of the baseline-category logit modelling for PA3 (Preference). The prefixes 1 to 5 correspond to the respective Likert levels of the variable.

IV	β_p	SE	$\hat{p}$
1~Intercept	-13.33	938.87	0.99
2~Intercept	-14.34	1728.99	0.99
4~Intercept	0.03	1.55	0.98
5~Intercept	0.42	1.74	0.81
1~so.L	-4.53	639.58	0.99
2~so.L	13.67	5467.53	1.00
4~so.L	1.14	1.23	0.36
5~so.L	0.92	1.45	0.53
1~so.Q	7.64	540.55	0.99
2~so.Q	-9.67	4620.91	1.00
4~so.Q	-0.01	1.01	0.99
5~so.Q	1.31	1.18	0.27
1~so.C	9.35	1279.16	0.99
2~so.C	6.29	2733.77	1.00
4~so.C	-1.51	0.75	0.04^{**}
5~so.C	-1.36	0.90	0.13
1~so.4	6.50	966.95	0.99
2~so.4	-2.80	1033.27	1.00
4~so.4	0.05	0.50	0.93
5~so.4	0.24	0.63	0.70
1~us.L	-4.00	667.69	1.00
2~us.L	-1.02	1.49	0.49
4~us.L	-0.11	0.95	0.91
5~us.L	1.16	1.69	0.49
1~us.Q	0.10	564.30	1.00
2~us.Q	-0.80	1.31	0.54
4~us.Q	-0.54	0.76	0.48
5~us.Q	-1.44	1.40	0.31
1~us.C	12.01	1335.37	0.99
2~us.C	0.50	1.10	0.65
4~us.C	1.54	0.67	0.02^{**}
5~us.C	1.76	1.02	0.08^{*}
1~us.4	8.30	1009.44	0.99
2~us.4	-0.37	0.80	0.64
4~us.4	-1.22	0.54	0.02^{**}
5~us.4	-1.24	0.73	0.09^{*}
1~ae.L	-1.27	1.98	0.52
2~ae.L	-0.07	1.73	0.97
4~ae.L	0.22	1.43	0.88
5~ae.L	-0.97	1.42	0.50
1~ae.Q	11.47	1538.73	0.99
2~ae.Q	1.72	1.43	0.23
4~ae.Q	1.33	1.22	0.28
5~ae.Q	2.82	1.23	0.02^{**}
1~ae.C	-1.58	2.46	0.52
2~ae.C	-0.67	1.16	0.56
4~ae.C	0.16	0.80	0.84
5~ae.C	-0.45	0.86	0.60
1~ae.4	-10.41	2064.42	1.00
2~ae.4	1.22	0.78	0.11
4~ae.4	-0.16	0.49	0.75
5~ae.4	0.30	0.58	0.60
1~ac.L	-7.41	721.17	0.99
2~ac.L	-1.76	1.62	0.28
4~ac.L	0.64	1.06	0.55
5~ac.L	1.04	1.40	0.46
1~ac.Q	4.89	609.50	0.99
2~ac.Q	-0.41	1.46	0.78
4~ac.Q	0.57	0.91	0.53
5~ac.Q	0.22	1.17	0.85
1~ac.C	11.76	1442.34	0.99
2~ac.C	0.24	1.12	0.83
4~ac.C	0.12	0.69	0.86
5~ac.C	1.00	0.85	0.24
1~ac.4	6.13	1090.31	1.00
2~ac.4	-0.09	0.77	0.91
4~ac.4	0.02	0.52	0.97
5~ac.4	-0.20	0.62	0.74
1~pca1	0.16	0.49	0.75
2~pca1	0.36	0.27	0.17
4~pca1	0.48	0.20	$\leq 0.01^{***}$
5~pca1	0.31	0.22	0.16
1~pca2	0.71	3.09	0.82
2~pca2	-4.66	2.47	0.06^{*}
4~pca2	0.60	0.84	0.47
5~pca2	0.82	0.94	0.39

(a) PA3: Preference

(b) PA3 (continued)

Hosmer–Lemeshow: $\chi^2_{32} \geq 100, p \leq 0.01$
Nagelkerke $R^2 = 0.42$

Table D4. Results of the baseline-category logit modelling for PI1 (Personification). The prefixes 1 to 5 correspond to the respective Likert levels of the variable.

IV	β_p	SE	$\hat{p}$
1∼Intercept	0.78	3.48	0.82
2∼Intercept	-12.50	1467.93	0.99
4∼Intercept	0.77	1.54	0.62
5∼Intercept	-2.31	1397.91	1.00
1∼so.L	19.62	3476.59	1.00
2∼so.L	-49.25	5591.13	0.99
4∼so.L	22.23	3476.59	0.99
5∼so.L	-20.11	3955.71	1.00
1∼so.Q	-15.29	2938.26	1.00
2∼so.Q	11.76	4725.37	1.00
4∼so.Q	-16.96	2938.26	1.00
5∼so.Q	18.88	3343.18	1.00
1∼so.C	11.35	1738.30	0.99
2∼so.C	-24.75	2795.56	0.99
4∼so.C	9.65	1738.30	1.00
5∼so.C	-11.49	1977.85	1.00
1∼so.4	-3.92	657.01	1.00
2∼so.4	2.86	1056.62	1.00
4∼so.4	-4.18	657.01	0.99
5∼so.4	4.47	747.56	1.00
1∼us.L	-1.80	2.23	0.42
2∼us.L	33.01	40837.20	1.00
4∼us.L	0.04	0.98	0.97
5∼us.L	9.64	2837.71	1.00
1∼us.Q	-0.58	1.77	0.74
2∼us.Q	-28.37	34513.73	1.00
4∼us.Q	0.49	0.81	0.54
5∼us.Q	-8.19	2398.30	1.00
1∼us.C	-1.14	1.39	0.41
2∼us.C	16.61	20418.60	1.00
4∼us.C	0.25	0.67	0.71
5∼us.C	5.41	1418.85	1.00
1∼us.4	0.87	1.10	0.43
2∼us.4	-6.29	7717.51	1.00
4∼us.4	-0.93	0.58	0.11
5∼us.4	-2.44	536.28	1.00
1∼ae.L	-10.77	2380.63	1.00
2∼ae.L	-20.10	2754.18	0.99
4∼ae.L	-9.73	2380.63	1.00
5∼ae.L	33.97	5792.73	1.00
1∼ae.Q	9.35	2012.00	1.00
2∼ae.Q	15.52	2327.71	0.99
4∼ae.Q	8.91	2012.00	1.00
5∼ae.Q	-27.02	4895.75	1.00
1∼ae.C	-4.75	1190.32	1.00
2∼ae.C	-8.57	1377.09	1.00
4∼ae.C	-4.53	1190.32	1.00
5∼ae.C	17.49	2896.37	1.00
1∼ae.4	1.21	449.90	1.00
2∼ae.4	3.10	520.49	1.00
4∼ae.4	1.20	449.90	1.00
5∼ae.4	-6.79	1094.72	1.00
1∼ac.L	-9.92	2533.63	1.00
2∼ac.L	28.25	40996.83	1.00
4∼ac.L	-10.84	2533.63	1.00
5∼ac.L	-10.69	2533.63	1.00
1∼ac.Q	8.87	2141.31	1.00
2∼ac.Q	-23.49	34648.65	1.00
4∼ac.Q	9.86	2141.31	1.00
5∼ac.Q	10.19	2141.31	1.00
1∼ac.C	-4.91	1266.81	1.00
2∼ac.C	13.37	20498.42	1.00
4∼ac.C	-6.24	1266.81	1.00
5∼ac.C	-5.91	1266.81	1.00
1∼ac.4	1.47	478.81	1.00
2∼ac.4	-4.35	7747.67	1.00
4∼ac.4	2.54	478.81	1.00
5∼ac.4	3.31	478.81	0.99
1∼pca1	-2.40	1.47	0.10^{*}
2∼pca1	0.08	0.20	0.69
4∼pca1	0.37	0.16	0.02^{**}
5∼pca1	0.25	0.18	0.16
1∼pca2	-1.71	2.17	0.43
2∼pca2	-1.17	1.42	0.41
4∼pca2	1.23	0.82	0.13
5∼pca2	1.58	0.99	0.11

(a) PI1: Personification

(b) PI1 (continued)

Hosmer–Lemeshow: $\chi^2_{32} \geq 100, p \leq 0.01$
Nagelkerke $R^2 = 0.41$

Table D5. Results of the baseline-category logit modelling for PI2 (Oneself). The prefixes 1 to 5 correspond to the respective Likert levels of the variable.

IV	β_p	SE	$\hat{p}$	IV	β_p	SE	$\hat{p}$
1~Intercept	-25.09	1572.83	0.99	4~ae.L	-12.01	4473.51	1.00
2~Intercept	-4.78	2619.48	1.00	5~ae.L	23.81	8506.49	1.00
4~Intercept	-0.75	2979.56	1.00	1~ae.Q	3.84	4916.25	1.00
5~Intercept	-0.96	2225.05	1.00	2~ae.Q	-17.18	27587.52	1.00
1~so.L	14.28	4473.52	1.00	4~ae.Q	11.09	3780.81	1.00
2~so.L	-34.02	9241.27	1.00	5~ae.Q	-19.03	7189.30	1.00
4~so.L	24.52	10430.24	1.00	1~ae.C	-14.59	2908.49	1.00
5~so.L	-21.83	6930.19	1.00	2~ae.C	0.22	15979.29	1.00
1~so.Q	4.91	4598.08	1.00	4~ae.C	-5.35	2236.76	1.00
2~so.Q	29.06	7810.30	1.00	5~ae.C	12.92	4253.25	1.00
4~so.Q	-20.06	8815.16	1.00	1~ae.4	2.34	1099.31	1.00
5~so.Q	20.52	5857.08	1.00	2~ae.4	-3.66	6168.76	1.00
1~so.C	5.32	2236.76	1.00	4~ae.4	2.07	845.41	1.00
2~so.C	-17.11	4620.63	1.00	5~ae.4	-5.14	1607.58	1.00
4~so.C	10.80	5215.12	1.00	1~ac.L	-12.68	3198.24	1.00
5~so.C	-13.03	3465.09	1.00	2~ac.L	14.13	23507.79	1.00
1~so.4	-15.91	3611.21	1.00	4~ac.L	0.98	1.04	0.34
2~so.4	7.46	1746.44	1.00	5~ac.L	0.68	1.06	0.52
4~so.4	-4.30	1971.13	1.00	1~ac.Q	-10.40	2703.02	1.00
5~so.4	4.89	1309.68	1.00	2~ac.Q	-11.34	19867.71	1.00
1~us.L	-15.34	3435.29	1.00	4~ac.Q	0.44	0.89	0.62
2~us.L	21.96	21491.72	1.00	5~ac.Q	0.54	0.93	0.56
4~us.L	0.57	0.96	0.56	1~ac.C	11.12	3443.38	1.00
5~us.L	11.24	5017.50	1.00	2~ac.C	5.63	11753.90	1.00
1~us.Q	-6.79	2903.40	1.00	4~ac.C	-0.07	0.69	0.92
2~us.Q	-19.90	18163.82	1.00	5~ac.C	-0.64	0.78	0.41
4~us.Q	0.40	0.77	0.61	1~ac.4	5.91	2139.28	1.00
5~us.Q	-8.37	4240.56	1.00	2~ac.4	-1.43	4442.56	1.00
1~us.C	-5.36	1717.65	1.00	4~ac.4	0.71	0.53	0.18
2~us.C	11.39	10745.86	1.00	5~ac.4	1.10	0.62	0.08$*$
4~us.C	0.09	0.68	0.90	1~pca1	-0.36	1.11	0.75
5~us.C	6.34	2508.75	1.00	2~pca1	-0.03	0.21	0.88
1~us.4	-3.50	649.23	1.00	4~pca1	0.11	0.14	0.42
2~us.4	-5.09	4061.55	1.00	5~pca1	0.06	0.16	0.70
4~us.4	-0.53	0.55	0.33	1~pca2	-3.40	5.20	0.51
5~us.4	-3.12	948.22	1.00	2~pca2	2.06	1.40	0.14
1~ae.L	-27.11	5816.98	1.00	4~pca2	2.00	0.90	0.03**
2~ae.L	-2.96	31958.58	1.00	5~pca2	2.02	0.98	0.04**

(a) PI2: Oneself (b) PI2 (continued)

Hosmer–Lemeshow: $\chi^2_{32} \geq 100, p \leq 0.01$
Nagelkerke $R^2 = 0.45$

Table D6. Results of the baseline-category logit modelling for PI3 (Materialisation). The prefixes 1 to 5 correspond to the respective Likert levels of the variable.

IV	β_p	SE	$\hat{p}$
1~Intercept	-17.40	1058.84	0.99
2~Intercept	-8.68	1811.93	1.00
4~Intercept	3.11	1.57	0.05^{**}
5~Intercept	-3.77	2241.51	1.00
1~so.L	-2.94	620.98	1.00
2~so.L	-12.65	4829.90	1.00
4~so.L	1.05	1.33	0.43
5~so.L	1.33	6592.13	1.00
1~so.Q	15.70	1533.85	0.99
2~so.Q	10.10	4082.01	1.00
4~so.Q	0.45	1.08	0.68
5~so.Q	0.86	5571.37	1.00
1~so.C	8.69	1241.94	0.99
2~so.C	-5.59	2414.95	1.00
4~so.C	-0.58	0.76	0.44
5~so.C	-0.87	3296.06	1.00
1~so.4	-4.39	2149.52	1.00
2~so.4	2.62	912.77	1.00
4~so.4	0.01	0.51	0.98
5~so.4	0.52	1245.80	1.00
1~us.L	-6.02	658.69	0.99
2~us.L	21.66	6213.39	1.00
4~us.L	-0.45	0.90	0.62
5~us.L	11.19	4998.06	1.00
1~us.Q	1.74	556.69	1.00
2~us.Q	-18.47	5251.27	1.00
4~us.Q	0.76	0.72	0.29
5~us.Q	-8.64	4224.14	1.00
1~us.C	12.01	1317.36	0.99
2~us.C	10.79	3106.69	1.00
4~us.C	0.42	0.61	0.49
5~us.C	6.22	2499.03	1.00
1~us.4	7.36	995.83	0.99
2~us.4	-3.56	1174.22	1.00
4~us.4	-0.67	0.53	0.21
5~us.4	-2.26	944.55	1.00
1~ae.L	-1.26	1.91	0.51
2~ae.L	-1.48	1.79	0.41
4~ae.L	0.00	1.28	1.00
5~ae.L	11.12	4206.98	1.00
1~ae.Q	10.72	1452.94	0.99
2~ae.Q	0.81	1.54	0.60
4~ae.Q	1.56	1.11	0.16
5~ae.Q	-7.21	3555.55	1.00
1~ae.C	0.16	2.76	0.95
2~ae.C	-0.60	1.07	0.57
4~ae.C	0.17	0.75	0.82
5~ae.C	6.12	2103.49	1.00
1~ae.4	-10.31	1949.33	1.00
2~ae.4	-0.47	0.67	0.48
4~ae.4	-0.95	0.50	0.06^{*}
5~ae.4	-2.99	795.04	1.00
1~ac.L	-7.06	719.27	0.99
2~ac.L	10.13	4189.61	1.00
4~ac.L	1.07	1.05	0.31
5~ac.L	0.21	1.01	0.84
1~ac.Q	3.58	607.89	1.00
2~ac.Q	-9.24	3540.86	1.00
4~ac.Q	-0.45	0.89	0.62
5~ac.Q	0.15	0.89	0.87
1~ac.C	9.31	1438.53	0.99
2~ac.C	4.93	2094.80	1.00
4~ac.C	-0.30	0.67	0.65
5~ac.C	-0.38	0.73	0.60
1~ac.4	8.35	1087.43	0.99
2~ac.4	-0.95	791.76	1.00
4~ac.4	1.11	0.54	0.04^{**}
5~ac.4	1.09	0.64	0.09^{*}
1~pca1	0.10	0.89	0.91
2~pca1	-0.22	0.24	0.35
4~pca1	0.14	0.13	0.30
5~pca1	-0.09	0.18	0.59
1~pca2	-0.31	4.03	0.94
2~pca2	-1.21	1.59	0.45
4~pca2	1.90	0.85	0.03^{**}
5~pca2	1.87	0.96	0.05^{**}

(a) PI3: Materialisation (b) PI3 (continued)

Hosmer–Lemeshow: $\chi^2_{32} \geq 100, p \leq 0.01$
Nagelkerke $R^2 = 0.42$

Table D7. Results of the baseline-category logit modelling for PD1 (Suitability). The prefixes 1 to 5 correspond to the respective Likert levels of the variable.

IV	β_p	SE	$\hat{p}$
1~Intercept	-74.30	2540.09	0.98
2~Intercept	-17.14	5684.02	1.00
4~Intercept	1.38	1.30	0.29
5~Intercept	-10.82	6250.56	1.00
1~so.L	-12.43	4074.59	1.00
2~so.L	14.25	11822.97	1.00
4~so.L	-0.13	0.96	0.89
5~so.L	12.67	13040.59	1.00
1~so.Q	3.05	3443.65	1.00
2~so.Q	-10.04	9992.24	1.00
4~so.Q	0.31	0.76	0.69
5~so.Q	-9.10	11021.31	1.00
1~so.C	28.61	8149.17	1.00
2~so.C	8.31	5911.49	1.00
4~so.C	-0.14	0.59	0.81
5~so.C	5.53	6520.30	1.00
1~so.4	15.87	6160.19	1.00
2~so.4	-1.82	2234.33	1.00
4~so.4	0.03	0.44	0.94
5~so.4	-2.43	2464.44	1.00
1~us.L	7.22	7964.20	1.00
2~us.L	-1.75	1.24	0.16
4~us.L	0.28	0.90	0.76
5~us.L	12.22	10178.41	1.00
1~us.Q	-0.57	7452.74	1.00
2~us.Q	1.14	1.04	0.27
4~us.Q	0.65	0.74	0.38
5~us.Q	-8.81	8602.33	1.00
1~us.C	-15.57	4133.15	1.00
2~us.C	-0.58	0.88	0.51
4~us.C	0.09	0.60	0.88
5~us.C	5.71	5089.21	1.00
1~us.4	-39.28	3972.79	0.99
2~us.4	-0.57	0.76	0.45
4~us.4	-0.05	0.48	0.92
5~us.4	-1.66	1923.54	1.00
1~ae.L	-34.57	8335.93	1.00
2~ae.L	11.31	9740.22	1.00

(a) PD1: Suitability

IV	β_p	SE	$\hat{p}$
4~ae.L	0.43	1.01	0.67
5~ae.L	-0.38	1.18	0.75
1~ae.Q	8.03	7644.53	1.00
2~ae.Q	-9.54	8231.99	1.00
4~ae.Q	0.29	0.86	0.73
5~ae.Q	1.07	1.03	0.30
1~ae.C	-15.91	4167.97	1.00
2~ae.C	3.89	4870.11	1.00
4~ae.C	-0.36	0.61	0.56
5~ae.C	-0.18	0.78	0.82
1~ae.4	-15.04	4337.82	1.00
2~ae.4	0.36	1840.73	1.00
4~ae.4	0.00	0.44	1.00
5~ae.4	0.07	0.59	0.91
1~ac.L	-17.38	8106.26	1.00
2~ac.L	9.56	9403.52	1.00
4~ac.L	0.45	0.78	0.57
5~ac.L	12.35	10818.48	1.00
1~ac.Q	15.44	7374.48	1.00
2~ac.Q	-10.97	7947.43	1.00
4~ac.Q	0.03	0.67	0.96
5~ac.Q	-10.56	9143.28	1.00
1~ac.C	7.12	4196.03	1.00
2~ac.C	7.49	4701.76	1.00
4~ac.C	-0.11	0.57	0.85
5~ac.C	6.47	5409.24	1.00
1~ac.4	-19.47	4291.31	1.00
2~ac.4	-2.52	1777.10	1.00
4~ac.4	0.02	0.48	0.96
5~ac.4	-2.09	2044.50	1.00
1~pca1	2.27	1.35	0.09*
2~pca1	0.09	0.22	0.69
4~pca1	0.18	0.12	0.16
5~pca1	-0.04	0.19	0.82
1~pca2	-14.65	8.34	0.08*
2~pca2	-2.24	2.13	0.29
4~pca2	1.04	0.72	0.15
5~pca2	0.61	0.92	0.51

(b) PD1 (continued)

Hosmer–Lemeshow: $\chi^2_{32} \geq 100, p \leq 0.01$
Nagelkerke $R^2 = 0.42$

Table D8. Results of the baseline-category logit modelling for PD2 (Uniqueness). The prefixes 1 to 5 correspond to the respective Likert levels of the variable.

IV	β_p	SE	$\hat{p}$	IV	β_p	SE	$\hat{p}$
1∼Intercept	-6.44	3.33	0.05**	4∼ae.L	12.47	1105.08	0.99
2∼Intercept	-10.58	523.49	0.98	5∼ae.L	-0.84	1.16	0.47
4∼Intercept	-4.24	349.46	0.99	1∼ae.Q	-0.95	1.55	0.54
5∼Intercept	-2.00	1.92	0.30	2∼ae.Q	-7.27	801.20	0.99
1∼so.L	0.46	1.27	0.72	4∼ae.Q	-9.42	933.96	0.99
2∼so.L	9.07	1045.25	0.99	5∼ae.Q	1.24	1.01	0.22
4∼so.L	0.03	1.21	0.98	1∼ae.C	-1.90	1.25	0.13
5∼so.L	0.48	1.45	0.74	2∼ae.C	4.15	473.99	0.99
1∼so.Q	0.16	1.12	0.89	4∼ae.C	5.84	552.54	0.99
2∼so.Q	-6.66	883.40	0.99	5∼ae.C	-0.43	0.88	0.62
4∼so.Q	0.32	1.00	0.75	1∼ae.4	0.44	0.81	0.59
5∼so.Q	1.87	1.22	0.13	2∼ae.4	-1.99	179.15	0.99
1∼so.C	1.46	0.96	0.13	4∼ae.4	-3.00	208.84	0.99
2∼so.C	3.28	522.63	0.99	5∼ae.4	0.35	0.67	0.60
4∼so.C	-0.72	0.77	0.35	1∼ac.L	-0.61	1.73	0.73
5∼so.C	-1.29	1.07	0.23	2∼ac.L	-1.11	1.09	0.31
1∼so.4	-0.67	0.78	0.39	4∼ac.L	-0.23	1.12	0.84
2∼so.4	-1.73	197.53	0.99	5∼ac.L	-0.31	1.74	0.86
4∼so.4	-0.41	0.54	0.44	1∼ac.Q	-0.32	1.54	0.84
5∼so.4	-0.21	0.83	0.80	2∼ac.Q	0.69	0.93	0.46
1∼us.L	-2.32	1.29	0.07*	4∼ac.Q	0.58	0.96	0.54
2∼us.L	6.96	865.53	0.99	5∼ac.Q	-0.94	1.48	0.52
4∼us.L	-1.16	1.12	0.30	1∼ac.C	1.25	1.16	0.28
5∼us.L	0.43	1.97	0.83	2∼ac.C	-0.21	0.71	0.76
1∼us.Q	1.45	1.06	0.17	4∼ac.C	-0.91	0.80	0.25
2∼us.Q	-7.79	731.50	0.99	5∼ac.C	0.58	1.05	0.58
4∼us.Q	1.72	0.91	0.06*	1∼ac.4	-0.40	0.92	0.66
5∼us.Q	0.24	1.67	0.89	2∼ac.4	0.81	0.54	0.13
1∼us.C	-0.50	0.91	0.58	4∼ac.4	1.17	0.60	0.05**
2∼us.C	5.00	432.76	0.99	5∼ac.4	0.55	0.72	0.44
4∼us.C	-1.13	0.90	0.21	1∼pca1	0.05	0.22	0.81
5∼us.C	1.71	1.22	0.16	2∼pca1	0.02	0.15	0.89
1∼us.4	0.68	0.86	0.43	4∼pca1	0.10	0.13	0.44
2∼us.4	-2.04	163.57	0.99	5∼pca1	0.02	0.19	0.90
4∼us.4	0.51	0.70	0.46	1∼pca2	-2.62	1.74	0.13
5∼us.4	-0.77	0.94	0.41	2∼pca2	-1.29	0.92	0.16
1∼ae.L	0.33	1.79	0.86	4∼pca2	-0.13	0.76	0.86
2∼ae.L	9.57	947.99	0.99	5∼pca2	-0.43	1.03	0.68

(a) PD2: Uniqueness (b) PD2 (continued)

Hosmer–Lemeshow: $\chi^2_{32} \geq 100, p \leq 0.01$
Nagelkerke $R^2 = 0.27$

Table D9. Results of the baseline-category logit modelling for PD3 (Affordance). The prefixes 1 to 5 correspond to the respective Likert levels of the variable.

IV	β_p	SE	$\hat{p}$	IV	β_p	SE	$\hat{p}$
1~Intercept	-31.49	752.24	0.97	4~ae.L	-0.37	1.04	0.72
2~Intercept	-20.25	2519.23	0.99	5~ae.L	0.27	1.21	0.82
4~Intercept	1.17	1.47	0.43	1~ae.Q	-7.20	1114.20	0.99
5~Intercept	-0.43	1.77	0.81	2~ae.Q	-9.67	3467.52	1.00
1~so.L	-5.52	664.98	0.99	4~ae.Q	-0.20	0.87	0.82
2~so.L	7.83	4248.48	1.00	5~ae.Q	0.49	1.06	0.64
4~so.L	0.69	1.11	0.54	1~ae.C	-7.11	659.11	0.99
5~so.L	-0.24	1.23	0.84	2~ae.C	3.99	2051.41	1.00
1~so.Q	4.05	562.02	0.99	4~ae.C	-0.62	0.62	0.32
2~so.Q	-7.07	3590.62	1.00	5~ae.C	-0.46	0.79	0.56
4~so.Q	0.21	0.90	0.82	1~ae.4	1.86	249.15	0.99
5~so.Q	0.75	1.01	0.46	2~ae.4	-0.55	775.36	1.00
1~so.C	13.26	1329.96	0.99	4~ae.4	0.33	0.47	0.47
2~so.C	4.73	2124.24	1.00	5~ae.4	0.11	0.61	0.86
4~so.C	-0.53	0.71	0.45	1~ac.L	-14.22	1004.21	0.99
5~so.C	-0.26	0.78	0.74	2~ac.L	9.16	3884.33	1.00
1~so.4	4.54	1005.36	1.00	4~ac.L	-0.09	0.96	0.92
2~so.4	-2.14	802.89	1.00	5~ac.L	0.00	1.25	1.00
4~so.4	0.31	0.51	0.54	1~ac.Q	-4.77	848.71	1.00
5~so.4	-0.64	0.60	0.28	2~ac.Q	-7.87	3282.86	1.00
1~us.L	-11.81	1070.66	0.99	4~ac.Q	0.77	0.80	0.33
2~us.L	10.29	3673.47	1.00	5~ac.Q	-0.13	1.06	0.90
4~us.L	1.27	0.91	0.16	1~ac.C	-5.32	502.11	0.99
5~us.L	1.82	1.31	0.17	2~ac.C	5.65	1942.17	1.00
1~us.Q	-10.28	904.90	0.99	4~ac.C	0.45	0.64	0.48
2~us.Q	-8.87	3104.65	1.00	5~ac.C	0.22	0.79	0.78
4~us.Q	-0.05	0.73	0.94	1~ac.4	-3.18	189.79	0.99
5~us.Q	0.37	1.11	0.74	2~ac.4	-1.98	734.07	1.00
1~us.C	-5.63	535.33	0.99	4~ac.4	0.08	0.50	0.88
2~us.C	6.68	1836.74	1.00	5~ac.4	-0.01	0.60	0.99
4~us.C	0.22	0.66	0.73	1~pca1	1.18	0.57	0.04^{**}
5~us.C	0.91	0.89	0.31	2~pca1	-0.18	0.37	0.64
1~us.4	-4.56	202.36	0.98	4~pca1	0.21	0.15	0.16
2~us.4	-2.25	694.22	1.00	5~pca1	-0.19	0.23	0.40
4~us.4	-0.13	0.52	0.80	1~pca2	-6.98	5.71	0.22
5~us.4	-0.09	0.69	0.89	2~pca2	-4.11	2.25	0.07^{*}
1~ae.L	-7.45	1318.22	1.00	4~pca2	0.93	0.81	0.25
2~ae.L	9.79	4102.82	1.00	5~pca2	-0.29	0.95	0.76

(a) PD3: Affordance (b) PD3 (continued)

Hosmer–Lemeshow: $\chi^2_{32} \geq 100, p \leq 0.01$
Nagelkerke $R^2 = 0.42$