AI for Inclusive Learning in Higher Education: Diversity, Accessibility, and Mental Health

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Abstract. The paper addresses the role of artificial intelligence (AI) in promoting inclusive and diversity-aware learning environments in higher education. It emphasizes the importance of equal access to education, especially for people with different abilities and backgrounds.
The narrative paper explores inclusive learning, personalized learning, adaptive learning through AI, and user models for inclusion. It emphasizes the diversity of learners, study-related disabilities, and the challenges of mental health in higher education.
Examples of AI applications in the areas of adaptive learning, improving accessibility, and supporting mental health are presented. In addition, an outlook on future developments is given, highlighting the positive potential of AI in creating inclusive learning environments while pointing out the challenges related to addressing diversity and inclusion.

KI für Inklusives Lernen in der Hochschule: Diversität, Barrierefreiheit und psychische Gesundheit

Zusammenfassung. Dieser Beitrag befasst sich mit der Rolle von künstlicher Intelligenz (KI) in der Förderung inklusiver und diversitätsbewusster Lernumgebungen in der Hochschulbildung. Es unterstreicht die Bedeutung eines gleichberechtigten Zugangs zur Bildung, insbesondere für Menschen mit unterschiedlichen Fähigkeiten und Hintergründen.
Der Artikel befasst sich mit inklusivem Lernen, personalisiertem Lernen, adaptivem Lernen durch KI und Nutzer*innenmodellen für Inklusion. Betont werden die Vielfalt der Lernenden, studienrelevante Beeinträchtigungen und die Herausforderungen der psychischen Gesundheit in der Hochschulbildung.
Es werden Beispiele für KI-Anwendungen in den Bereichen adaptives Lernen, Verbesserung der Barrierefreiheit und Unterstützung der psychischen Gesundheit vorgestellt. Darüber hinaus wird ein Ausblick auf künftige Entwicklungen gegeben, der das positive Potenzial der KI bei der Schaffung inklusiver Lernumgebungen hervorhebt und gleichzeitig auf die Herausforderungen im Zusammenhang mit der Berücksichtigung von Vielfalt und Inklusion hinweist.

1 Introduction

Education is a fundamental human right and essential for personal development. Therefore, it is necessary to provide equal access to education, especially for people with different abilities and backgrounds. The latest breakthroughs in generative artificial intelligence (AI) intensified the discourse on AI in higher education, which comprises the role of AI in supporting personalized learning and thus the provision of individual support, the future role of teachers and classrooms, ethical concerns in using AI in education, as well as the possible takeover of routine tasks in education.
The impact of innovations in educational technology on various aspects of learning has been a topic of discussion for quite some time. In particular, the discourse has focused on promoting active learning, individualization, multi-sensory delivery, and flexibility for learners with special needs (Tezcan 2014). When integrating AI into higher education, the following goals have emerged: automatic assessment and feedback, support for adaptive learning, and learning analytics (Pinkwart and Beudt 2020; Witt, Rampelt, and Pinkwart 2020). In addition, the potential of educational technologies extends to improving teaching productivity, facilitating distance learning, creating virtual classrooms, and supporting students with disabilities (Haleem et al. 2022). However, among discussions about individualization, the concept of inclusive learning, i.e., ensuring that all people, regardless of their different backgrounds or abilities, have equal access to education and the same learning opportunities, is often overlooked. For this reason, this paper discusses the role of AI in promoting an inclusive and diversity-aware learning environment in higher education (HE).
Inclusive learning, as a commitment to equal opportunities for all, requires alignment with politics, pedagogy, curriculum, assessment, and technology (Lawrie et al. 2017; Hockings 2010). However, we focus on the aspect of how potential AI-based applications in higher education teaching can promote inclusion, particularly in implementing personalized learning, improving accessibility, and promoting mental health.
To this end, we first discuss the terminology in section 2. Section 3 looks at possible user models that enable personalized learning through AI. We highlight the diversity of learners, the study-affecting impairments, and the impact of students' mental health status on learning performance. Sections 4-6 present examples of AI-based applications for adaptive learning, accessibility enhancement, and mental health support. Finally, future developments and challenges are discussed, and the paper is concluded.

2 Inclusive Learning and Personalized Learning

Before discussing the role of AI in promoting inclusion in higher education, the terms inclusive learning and personalized learning will first be defined, as the terminologies reveal similarities that are fundamental to further considerations in this paper.

2.1 Inclusive Learning

Various perspectives on the concept of inclusion and inclusive learning exist. This paper adopts the concept of inclusion, which encompasses all people, including those with a disability. By this understanding, the authors refer to the definition provided by UNESCO, and specifically, to Hockings' synthesis:

> "Inclusive learning and teaching in higher education refers to the ways in which pedagogy, curricula, and assessment are designed and delivered to engage students in learning that is meaningful, relevant, and accessible to all" (Hockings 2010, 1)

In this comprehensive perspective, students with diverse learning needs, students facing disabilities, students with impairments, chronic diseases, or health problems, students from different faith backgrounds, diverse cultural identities, and various sexual orientations are encompassed. This perspective also considers whether students are studying full-time or part-time, possess different professional and personal life experiences, or have different lifestyles and distinct approaches to learning. Even though universities are committed to diversity, the practical implementation of equal opportunities in education remains a challenge. Personalized learning, which focuses on adaptive and differentiated learning at the micro level, has been touted as one solution to this problem.

2.2 Personalized Learning

Personalized learning is a concept that can promote people's skills development and support self-directed learning, as it involves personalized learning experiences according to individual learning goals, abilities, and preferences. The concept is continuously discussed in education and against the background of a rapidly changing (analog and digital) world with pluralistic living environments and technological advances in all areas of life, to enable people to learn in a competence-oriented way, which can promote agility and the ability for independent, self-organized and goal-oriented action (Fischer 2018).

Personalized and inclusive learning have strong parallels, especially in terms of the foundation to consider the individual. Personalized learning is also used synonymously with differentiation and individualization and can be understood as a specific concept that promotes inclusive learning.

Personalized learning can be considered at the policy, pedagogical, or learner levels. While central aspects such as learning goals and approaches are discussed at the policy and pedagogical level, the personalization of the learning path, the pace of learning, or the learning context are considered at the learner level. Personalized learning paths can be useful when learners differ in their experiences, personal interests, cognitive states, behaviors, and sensitivities. Personalized learning can likewise refer to the place of learning and means a continuum of learning with others at the same pace or quite individually (Holmes et al. 2018).

3 User Models for Adaptive Learning

In section two, we introduced the concept of inclusive and personalized learning and explained that personalized learning is one possible approach to promote inclusion.

If personalized learning is implemented by educational technologies, specifically through AI, we refer to it as *adaptive learning*. Adaptive learning support systems adjust their interaction, content, or appearance according to individual requirements and preferences of learners. The foundation of an adaptive system is the user model, which specifies the characteristics of the learner and allows derivations for customization options (so-called adaptations).

User models represent the differences between learners and provide evidence for developing learning assistants that behave differently for different learners. That requires sufficient knowledge about individual differences in abilities, preferences, or behavior that impact the learning experience and success.
In this section, we show examples of possible learner differences that motivate adaptive learning. We also show the high diversity of people who have a study-affecting impairment, and we specifically address the high prevalence of students with mental health problems, as this results in a variety of requirements for an inclusive learning environment.

3.1 Learner Diversity

Learner diversity encompasses a wide spectrum of factors, including cultural and linguistic diversity, cognitive and learning style diversity, as well as socioeconomic diversity. In the following, we provide examples of varying learner aspects, which can be a foundational rationale for personalized learning. We do not discuss the full range of diversity in learning as this has been well documented (cf. National Research Council 2018, 2000.
All people learn differently and bring their individual expectations, experiences, personal learning methods, prior knowledge, and goals into the learning process (Fischer 2018).
Learners from different cultures may, for instance, vary in their reasoning about intelligence and thus differ in their understanding of required learning competencies and success. For instance, a study showed that while U.S. parents assess deviation from a model as showing creativity, parents in Vanuatu tend to assess precise imitation with intelligence (Clegg, Wen, and Legare 2017). Early in life, community expectations strongly influence how children approach learning, how they think about themselves, and how they socially interact (Keller et al. 2009). Other studies provide evidence that cross-cultural differences play a role in varying cognitive processes, i.e., in terms of memory, perception, and attention (Cole 1995; Rogoff and Chavajay 1995; Segall, Campbell, and Herskovits 1996) and that culture also affects the cognitive processes that shape learning (National Research Council 2018). No two learners are exactly alike in their cognitive abilities and learning approaches.
Diversity can also be observed in the pace of learning, meaning the time it takes for a person to achieve a specific learning goal. The variations in learning pace are the greatest in adult education (e.g., higher education), where the heterogeneity of groups is increasing. Ranges up to a factor of nine are possible, meaning that slow learners may require up to nine times longer than fast learners need to achieve a learning goal (Wahl 2006). One reason for these enormous differences is primarily in the level of expertise. The level of expertise in a certain subject significantly impacts learning success and is highly individual. The level of expertise affects the way learners notice and how they organize, represent, and interpret information in their environment (National Research Council 2000). Other factors, such as talent and motivation, play a subordinate role (Wahl 2006).
Beyond individual learning differences or challenges, students learn in diverse learning contexts. Due to the coronavirus pandemic, particular research focus was put on the challenges and barriers students face by dominated digital learning. Diversity and common barriers comprise communication, technical barriers (e.g. due to insufficient

technical equipment or deficit of digital skills), financial situations, or care activities for family members (Gan and Sun 2021; Ulzheimer et al. 2021).

3.2 Study-affecting Impairments

The recent Best3 student survey conducted in Germany reveals that approximately 16 % of students have a study-affecting impairment, showcasing a high degree of diversity within this group (Kroher et al. 2023). For 56 % of these students, their impairment is not long-term perceptible to other people, while 44 % have perceptible impairments (Kroher et al. 2023)). Significantly, about 65 % of students facing a study-affecting impairment suffer from mental illnesses, a proportion that has been on steady incline since 2011 (Kroher et al. 2023; Deutsches Studentenwerk 2018; Poskowsky et al. 2018). This issue is specifically addressed in section 3.4, underscoring its importance.

Additional factors contributing to study difficulties include chronic illness, affecting 13 % of students. Furthermore, 1 to 4 % of students experience partial performance disorders or have a movement, visual or hearing impairment (Kroher et al. 2023). 92% of students with study-affecting impairments report encountering difficulties in organizing and carrying out their studies, as well as in examination and teaching situations (Kroher et al. 2023). The challenges in the area of study organization are most frequently attributed to the high density of exams, compulsory attendance requirements, and performance deadlines (Kroher et al. 2023; Deutsches Studentenwerk 2018; Poskowsky et al. 2018).

Hidden difficulties frequently emerge as well; for instance, students encounter challenges in social interactions, which can trigger or intensify problems in their studies. The fear of rejection and stigmatization, along with negative experiences related to coming out, complicates communication with teachers, fellow students, and administration staff (Deutsches Studentenwerk 2018; Poskowsky et al. 2018).

Globally, there are increasing numbers of students with learning difficulties related to neurodiversity, i.e., dyspraxia, dyslexia, attention deficit hyperactivity disorder, dyscalculia, autism, and Tourette syndrome. Students with learning disabilities often experience frustration, especially when required learning resources and tools are unavailable. They may feel isolated, stressed, anxious, unhappy, and overwhelmed when they do not find familiar structures, people, and environments in challenging situations. Students with dyslexia and ADHD often struggle with feelings of inadequacy, stigma, and difficulty with short-term memory, which impacts their academic and psychosocial performance and persistence in college. To cope with their stress and anxiety, they benefit from support services that are aligned with the diversity-sensitive design approach and accommodate diverse preferences, leisure activities, and appropriate rest and social learning (Clouder et al. 2020).

For many students with study-affecting impairments, accessibility is fundamental in the context of learning environments. Numerous digital barriers persist in our educational systems, restricting the pathways to knowledge for students or even excluding them from learning in general. These barriers comprise inaccessible content or education technology that unmet accessibility standards (cf. Web Content Accessibility Guidelines 2.2; W3C 2023). This inaccessibility can manifest in various ways, including a lack of alternative formats or complex learning structure material and navigation.

Many educational materials are still primarily presented in text or visual formats, making them challenging for individuals with visual impairments, dyslexia, or other learning-related disabilities. Learners with hearing impairments may encounter difficulties with multimedia content that lacks captions or transcripts, making audio and video materials inaccessible. Inaccessible learning websites and platforms may also occur due to complex or non-intuitive navigation, and confuse learners with cognitive disabilities, such as dyslexia or ADHD.

The digital learning landscape is characterized by heterogeneous technologies, devices, and software platforms. While this heterogeneity can provide opportunities for flexible learning, it also presents issues with robustness and compatibility with assistive technologies that can create barriers for certain learners. People with disabilities often rely on assistive technologies such as screen readers, magnifiers, voice recognition software, or special input devices. Compatibility issues between these assistive technologies and learning platforms can impede their access to educational content. Learners with motor impairments may experience barriers in operating digital interfaces that are not designed to be fully accessible. Beyond technical accessibility issues, specific barriers can occur in particular learning activities (Coughlan et al. 2019).

3.3 Mental Health of Students

The topic of mental health in higher education has increased in importance in recent years and needs to be addressed when discussing approaches for more inclusive learning. In 2018, the WHO studied 19 colleges in eight countries to investigate the prevalence of common mental disorders among first-year college students (Auerbach et al. 2018). Results showed a lifetime prevalence of 35 % and a twelve-month prevalence of 31 % of at least one of the screened disorders (i.e. major depression, generalized anxiety disorder, mania, panic disorder, alcohol use disorder, and substance use disorder) among participants. For students with non-heterosexual identification, the lifetime prevalence was as high as 76.5 %.

While those numbers already emphasize the severity of resulting challenges for the education sector, the prevalence of depression and anxiety has increased even further among students in higher education and the general population since then (Chang et al. 2021; Santomauro et al. 2021). This enlarges the already existing treatment gap in mental health care (Denecke, Vaaheesan, and Arulnathan 2021), resulting in long waiting lists and an increased burden on mental health facilities and colleges (Auerbach et al. 2018; Webb, Rosso, and Rauch 2017).

For the affected individual, mental illnesses can significantly affect academic performance (Hysenbegasi, Hass, and Rowland 2005; Mirawdali, Morrissey, and Ball 2018) and, among other negative consequences, lead to social isolation and loneliness (Yuan et al. 2022).

In the face of this rich diversity, a one-size-fits-all approach to education is no longer adequate. Instead, educational institutions increasingly need to turn to personalized and differentiated learning strategies to ensure that individual demands and challenges are properly addressed. How novel AI-based technologies can contribute to this demand is discussed in the next section.

4 AI-based Personalized Adaptive Learning in HE

Personalized learning supported by technology has a long history dating back to the twenties when the first learning machine was developed to review test items. Since the eighties, a wide variety of technologies and digital media have been developed to support personalized learning. These include intelligent tutorial systems (ITS), exploratory learning environments, intelligent learning management systems (LMS), learning network orchestrators, and digital learning games (cf. Holmes et al. 2018).
Many of these technological approaches (collectively known as adaptive learning systems) aim to support personalized learning. For a long period, adaptive learning systems were rather limited in their adaptivity approach to personalization and fell far short of what kind of personalization was needed (Harrigan et al. 2009).
Adaptive learning systems usually consist of a domain model, a learner model (user model), and a didactic model. Domains and didactics model formalizes domain knowledge and didactic concepts, which are the basis for adaptation. In the learner model, the characteristics of differentiation are mapped, such as the learning goals, the learning path, and the learning speed, which serve as the basis for personalization see section 3). Adaptive learning systems, like adaptive user interfaces, are characterized by different afference, efference, and inference mechanisms and require, concerning the application field of inclusion, the differentiated consideration of diversity and variability in the user model (Loitsch 2018).
Adaptive learning systems have significantly progressed with the advances in AI, AI-based learning tools, and AI-based learning analytics (Pelletier et al. 2022). Novel AI-based adaptive learning systems focus on clustering students and automatically detecting learner characteristics through machine learning. This area is commonly described as educational data mining (EDM).
EDM techniques can variously support recommendations and predictions of student performance, detection of undesirable behaviors, grouping of students, and analysis of social networks (Romero and Ventura 2010; Xiao, Ji, and Hu 2022). Further approaches focus on recognizing emotions and managing learners' contextual data (Santos, Kravcik, and Boticario 2016) or inferring contextual preferences directly from individuals' behavior (Unger et al. 2017). EDM techniques also open new horizons for AI-based learning tools supporting the acquisition of competencies and skills, for instance, by identifying learning progress through automated error detection and automatically generated individual feedback, which can support learners to achieve their envisaged learning competencies and the recommendations of individual learning paths (cf. Witt, Rampelt, and Pinkwart 2020).
While EDM's ability to cluster learners and identify characteristics through machine learning can enhance personalized education, it also raises concerns about privacy and the potential for stigmatization, particularly regarding sensitive information such as impairments or mental health status. This necessitates a careful balance between leveraging EDM's benefits and safeguarding students' privacy and well-being in educational settings.
A foundation of adaptive learning systems is the automated assessment of learning tasks (Pinkwart and Beudt, 2020) to provide individualized feedback on learning status, which is considered a prerequisite for self-directed learning (Butler and Winne 1995). Comprehensive performance-based tutoring has been developed with MathSpring. MathSpring analyzes the time students spend on tasks, what mistakes they

make, and what assistance they need to derive cognitive and metacognitive skills and, based on this, offers personalized motivational assistance and reflection on one's learning model to actively shape the learning process (Arroyo et al. 2014).
The relevance of mentoring to support metacognitive processes has been investigated by Lodge et al. They propose that nudging and prompting students to consider and reconsider their used learning strategies is more successful than just giving feedback about mistakes because it supports students better in their reflection and learning activation (Lodge et al. 2018). MetaTutor also addresses support for self-regulated learning by allowing learners to individually set intermediate goals for a learning session (Azevedo et al. 2010).
With the breakthrough of generative AI, writing assistants and learning-enhancing conversational agents, particularly chatbots, are increasingly being researched and developed. Advancements are evident in the form of recommender systems to provide decision support to students such as aiding in choosing a major (Obeid et al. 2018) or a university (Rivera, Tapia-Leon, and Lujan-Mora 2018), recommending courses (Aher and Lobo 2013), or suggesting resources (El-Bishouty et al. 2014). Additionally, these technologies are used to answer common study-related questions (Hien et al. 2018; Shukla and Verma 2019). The extent to which chatbots are suitable as training partners in question-answer dialogs is also currently being investigated, with initial studies indicating that the quality of conversations can be similar to those with human instructors (Ndukwe, Daniel, and Amadi 2019).
With its ability to adapt, predict, and personalize, AI has proven to be a powerful technology that enables more effective self-directed learning, as numerous research papers show. However, there is still a lack of empirical evidence that the widespread use of this type of learning assistant leads to a tangible improvement in inclusion.

5 AI-based Support to Improve Accessibility in HE

The potential of AI to overcome digital barriers in education and support inclusion for all students is also manifold (Mehigan 2020; Zdravkova 2022).
Advances in AI are continuously contributing to web accessibility in general (Abou-Zahra, Brewer, and Cooper 2018; Ara and Sik-Lanyi 2022). This progress can also contribute to making learning platforms and materials accessible to meet international standards (cf. Web Content Accessibility Guidelines 2.2; W3C 2023). For instance, constant progress is made in using AI for generating image text alternatives, generating image descriptions, providing video captions, or modifying the DOM (Document Object Model) to improve structure and source code directly (cf. Ara and Sik-Lanyi 2022). Other approaches to web accessibility also emerge, such as using chatbots to interact with a web page and to help find information (Suseela et al. 2021), applying AI-based text processing to support understanding web content more effectively, such as splitting long text into short text, summarizing text paragraphs or removing difficult words (Sarker 2021). AI-based web content detection is also applied to support screen readers in identifying relevant content (Mathur et al. 2021).
AI is continually getting better at providing automated translations in real-time. For learners with different language backgrounds, real-time translations can facilitate understanding and participation.

AI is also creating improvement and change in the field of special education. AI-powered augmentative and alternative communication (AAC) applications enable personalized speech communication support for people with language disabilities (Evangeline 2022; Konadl et al. 2023). AI-based potentials of AAC systems include maintaining the formal course of a conversation, incorporating natural context factors, tailoring communication toward the interlocutor, and adapting to speech impairments (Konadl et al. 2023).
Next to improving accessibility for students with impairments, AI technology can furthermore be leveraged to support the mental health of students in higher education.

6 AI-based Mental Health Support in HE

The increased demand for psycho-therapeutic counseling services at college institutions (Adam-Gutsch et al. 2021) makes it clear that new approaches must be found to better support students in their daily lives and explicitly include students with mental illnesses. Only in this way can it be ensured that students are optimally supported for their learning success and thus also for their academic success (Mirawdali, Morrissey, and Ball 2018). One possible solution could lie in the use of internet-based interventions – in addition to the already existing counseling services – as they are easy to access, discrete in usage, and scalable (Auerbach et al. 2018).
Research on internet-based therapy approaches, mostly based on cognitive behavioral therapy, has been going on for several decades, and studies yielded promising results in terms of acceptance and efficacy (Etzelmueller et al. 2020). Specifically for depression and anxiety, internet-based interventions can have comparable effects on disorder symptoms as conventional face-to-face therapy (Carlbring et al. 2018).
Since 2016 first systems emerged that combine internet-based therapy with AI-based systems (Abd-Alrazaq et al. 2019; McCashin, Coyle, and O'Reilly 2019; Milne-Ives et al. 2020). Next to making internet-based treatment more autonomous and, therefore, more cost-effective, AI-based systems can be leveraged to provide adaptive interventions, personalized treatment approaches (Mehta et al. 2021), an anonymous and automated solution for the screening of mental and emotional states, and triaging (Auerbach et al. 2018; Mehta et al. 2021).
Existing approaches have used AI-based chatbots and voice assistants to make exercises and psycho-educational content from cognitive behavioral therapy and positive psychology available to people in a low-threshold and interactive way (Abd-Alrazaq et al. 2019; McCashin, Coyle, and O'Reilly 2019; Milne-Ives et al. 2020). Next to therapy-based interventions, established systems such as WoeBot[1], Youper[2], and Wysa[3] can also be used to track the emotional and mental health state of users.
Moreover, in recent years, systems have been developed that specifically try to provide mental health coaching for students by eliciting self-reflection (Mai and Rutschmann 2023), and by leading the user through guided discovery and breathing exercises (Striegl et al. 2022) to cope with test anxiety. Thus far, conducted studies have shown a good acceptance of chatbot-based systems (Fitzpatrick, Darcy, and Vierhile

[1] WoeBot Inc., https://woebothealth.com/, accessed 30.10.2023
[2] Youper, https://www.youper.ai/, accessed 30.10.2023
[3] Wysa, https://www.wysa.com/, accessed 30.10.2023

2017; Mai and Rutschmann 2023) and voice assistants (Gotthardt et al. 2022; Striegl, Loitsch, and Weber 2023) among students.

In the context of inclusive learning in higher education, this makes the tailored support of students with mental health problems and the faster identification of such problems possible. As meta-cognitive, emotional, and motivational aspects play a crucial role in learning in addition to cognitive factors (Witt, Rampelt, and Pinkwart 2020) and as the mental health state significantly affects academic success (Hysenbegasi, Hass, and Rowland 2005; Mirawdali, Morrissey, and Ball 2018), those novel approaches should be used for the mental health support of students while taking ethical considerations and limitations into account (Carr 2020; D'Alfonso 2020).

7 Future Directions and Challenges

As we navigate the dynamic landscape of inclusive learning with AI, it is essential to look ahead to the future, anticipating emerging trends and potential challenges but also discussing the obstacles that may arise on the path to creating inclusive and diverse-aware learning environments.

7.1 Future Directions

AI will significantly impact the field of education (cf. Ikka 2018; Witt, Rampelt, and Pinkwart 2020; Pelletier et al. 2022; Schmohl, Watanabe, and Schelling 2023. The combination of AI-enhanced learning analytics and AI-powered learning assistants will continue to grow and mature (Pelletier et al. 2022) and will likely witness increased integration in all educational settings, driving automation of learning and teaching tasks. With regard to the frame of this paper, which is on fostering personalized and inclusive learning, we highlight the following directions for future research and development.

AI-based implementation of personalized learning should extend more to skills-based support, i.e., learner models should highlight students' strengths, abilities, and competencies rather than their weaknesses, errors, or underachievement. To accommodate diversity, especially neurodiversity, future AI models should support multiple learning paths and different interaction modalities. At the same time, it is relevant to investigate the appropriate level of adaptation to avoid potential over-personalization. In addition, AI research should be enhanced to support social learning and the activation process that occurs through social learning. In this respect, AI-enhanced learning can also promote more global approaches to learning, making cultural diversity in learning a promising research direction. Collaborative learning experiences that bring together students from different backgrounds are likely to become more common and promote intercultural understanding and integration (U.S. Department of Education and Office of Educational Technology 2023).

AI-powered learning assistants differ in their possibilities for interactions and create new user experiences for teachers and students, which implies expanding international standards and accessibility guidelines to meet the shift to more conversational user interfaces, including dialogues voice interfaces, but also more annotating and highlighting capabilities.

7.2 Potential Challenges

Despite the potential that AI-enabled applications offer for inclusive learning, numerous challenges remain, for example, digital equity, because not all learners have equal access to technology. Among other ethical considerations (Holmes and Porayska-Pomsta 2022), the following are relevant to EDM and AI-based learning assistants.
For all kinds of AI-empowered learning assistants, it is particularly important to ensure that the use is voluntary and that students can clearly recognize that the interaction partner is a program and not a human (Witt, Rampelt, and Pinkwart 2020). The collection and analysis of large amounts of data about learners provide the basis for many of the application areas discussed in this paper. Maintaining the privacy and security of the data will be an ongoing challenge. The role of human educators remains indispensable in education, especially for emotional support and mentoring. Balancing the benefits of AI with the need for human interaction in learning environments is challenging. Educational institutions should be involved in the development of AI-based educational technologies (Bates et al. 2020) with the accompaniment of sound empirical research (Holmes et al. 2018). Discussions about modern educational theories must also be participatory in the development process. For example, how assessment frameworks could look like that consider the diverse needs of learners will be critical.
As mentioned earlier, one of the potential future directions is to extend personalized learning through adaptive learning systems to support diversity and multiple learning contexts more comprehensively, which, at the same time, is a grant challenge because it requires interdisciplinary research and development from the field of educational, cognitive science, phycology, user experience design, and computer science.
Despite these challenges, the future of inclusive learning with AI is encouraging if advancements are aligned with the goals of inclusion and diversity awareness.

8 Conclusion

This paper explored the role of AI in the design of inclusive and diversity-aware learning environments.
In particular, we discussed the triad of learner diversity, study-affecting impairments, and new challenges posed by mental health issues in relation to the importance of inclusion in higher education. The paper presented potential research to promote inclusive learning through personalized adaptive learning assistants and support services.
To conclude, AI has great potential to promote inclusion due to its high flexibility, adaptability, and scalability. However, a prerequisite for success is that AI tools are designed from a human perspective, developed according to ethical principles, and empirically evaluated in comprehensive studies so that the use of AI leads to the promotion of individual learning and not to greater exclusion.

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