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Students' perceived impact of GenAI tools on learning and assessment in higher education: the role of individual AI competence

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Abstract

The adoption of artificial intelligence (AI) and generative artificial intelligence (GenAI) tools in higher education institutions (HEIs) raises numerous questions and application possibilities. This study included $N = 223$ students from HEIs across different countries and investigated students' AI competence and how they evaluated the specific benefits of several GenAI tools for learning and assessment. The GenAI tools included in the study were designed for different application contexts and purposes. The study goes beyond students' preferences by simultaneously adopting a broad approach that considers their AI competence, their perspectives on six different GenAI tools, and a focused approach that investigates the specific benefits of these tools in learning and assessment. The results indicate that the dimensions of AI competence vary considerably, significantly impacting how the GenAI tools were evaluated. Results also show that students perceived and evaluated the different tools according to their potential use in pursuing their study goals. This research calls for a more nuanced and differentiated analysis of AI approaches by different stakeholders in HEIs for the promotion of the enhancement of students' AI competence and awareness in using GenAI tools rather than amalgamating AI and GenAI tools under one banner and for understanding possible benefits and application of them in HE learning and assessment processes.

Keywords: Generative AI, AI in education, AI competence, Assessment

Introduction

The advances in artificial intelligence (AI) are rapidly and continuously transforming various contexts of people's lives, the higher education sector is not immune to being affected by these advances and their related changes. In this specific education sector, AI has a lot of potential, such as in analysing vast datasets to improve student outcomes, in personalising learning experiences, in rendering automated administrative tasks, and in providing adaptive learning (Bond et al., 2024). The confluence of these potentialities positions AI as a major emerging innovative factor in higher education, reshaping how current and future generations learn and teach in higher education institutions (HEIs). The rapid emergence of AI has resulted in research and practice in education being behind in unwrapping the full potential of AI compared to other disciplines, such as business or health (Luckin & Cukurova, 2019). From the incorporation of AI-powered adaptive learning environments by academic staff to the use of AI for the prediction and evaluation of student success by administrators and adaptive support whenever a student needs it, stakeholders across HEIs will inevitably encounter AI in different ways (Zawacki-Richter et al., 2019). However, most of these implementations are centred on using AI in instructors' assessments, although students can also employ AI-based tools to aid them. Accordingly, the presence of AI across the HEIs necessitates a dynamic interplay between different stakeholders and systems (Daugherty & Wilson, 2018; Ifenthaler & Schumacher, 2023). This engagement is crucial for fostering the development of AI competence—above all, among students. AI competence is the ability to comprehend, utilise, and critically evaluate AI tools (Kim et al., 2021), it allows stakeholders to gain skills and knowledge about AI, interact efficiently with AI, and make informed and productive decisions in implementing AI in their learning processes (Dai et al., 2023). Hence, AI competence in education is a set of skills that enable stakeholders to ethically and responsibly develop, apply, and evaluate AI for learning and teaching (Delcker et al., 2024).

In the scenario of AI application and utilisation, since late 2022, witnessed a surge in accessible generative artificial intelligence (GenAI) tools, defined as deep learning models trained on diverse datasets, such as large language models (LLMs), to process user prompts and create human-like outputs (Hsu & Ching, 2023). This emerging frontier launched a controversy surrounding the use of GenAI in schools and universities, with some viewing it as a beneficial tool and others expressing concern about its potential impact on education (Mamo et al., 2024). Previous research showed a simultaneously enthusiastic, as well as concerned, opinion of students towards the usage of GenAI tools in HEIs, such as ChatGPT (Baig & Yadegaridehkordi, 2024; Chan & Hu, 2023; Chiu et al., 2023). A unified response among HEIs has been to adapt learning and assessment environments as well as introduce regulations to make AI use more appropriate in this new age of GenAI (Bhullar et al., 2024; Foung et al., 2024). The assistance of GenAI, however, extends beyond the automatic completion of tasks; AI in HEIs has the potential to both hinder and create educational opportunities (Lim et al., 2023), such as increasing support for learners in tasks as a form of guidance while potentially making it more difficult for teachers to differentiate student performance when AI-generated material is involved. Furthermore, a central point of discourse is the call to action in reacting to the application of specifically GenAI in the form of language production to hinder plagiarism (Lo, 2023).

However, many aspects remain to be investigated and discovered about how students use GenAI in learning and assessment processes and what their views are regarding these tools. Accordingly, this study explores the issues surrounding GenAI in HEIs from an international student perspective. Particularly, the research team utilised an online instrument to investigate students' AI competence and their perceptions of a range of GenAI tools in the context of learning and assessment within HEIs. This research may critically evaluate students' perceptions of GenAI tools and uncover possible benefits and application scenarios that may be employed in higher education learning and assessment.

Background

Artificial intelligence competence

With the rise of AI in the context of education, the research into AI competence in education is simultaneously increasing rapidly (Sperling et al., 2024). The existing literature on AI competence identifies different skills, which can be summarized in distinctive competence dimensions. For instance, AI competence involves a basic understanding of the functionality of AI (Attwell et al., 2020), including identifying whether or not an application uses AI (Long & Magerko, 2020). Another dimension of AI competence is related to data security risks and data privacy assurance when collecting, analysing, and managing data in education (Papamitsiou et al., 2021). This emphasizes identifying the potential and risks of AI in education, society, and the workplace (Attwell et al., 2020). AI competence is fundamental, as it allows students to not only gain skills and knowledge about AI but also to interact efficiently with AI and make informed and productive decisions in implementing AI in their learning process (Dai et al., 2023). Huang (2021) proposed a framework that places a weighting on specific AI-related concepts, such as machine learning, robotics, and programming, in combination with more general key competencies (e.g., self-learning and teamwork). In contrast, Kim et al. (2021) established their model on the foundations of AI knowledge, AI skills, and AI attitudes, highlighting the significance of critical reflection on the ethical implementation of AI. Sanusi et al. (2022) adopted a similar approach, integrating the ethics of AI as a competence dimension that bridges the other dimensions of their model, namely learning, teamwork, and knowledge competence. Based on a systematic literature review as well as expert interviews, Delcker et al. (2024) developed a framework of AI competence in the context of education, including the subcomponents of theoretical knowledge, legal framework and ethics, implications of AI, attitude towards AI, teaching and learning with AI and ongoing professionalization as the cornerstone of a competent approach to AI. This framework is modular and can be adapted according to the target group.

Generative artificial intelligence tools

Since late 2022, there has been a rapid increase in the number and variety of GenAI tools available. GenAI is a term used to describe an advanced technology that integrates deep learning models, trained on extensive datasets gathered from various sources, which processes inputs (i.e., prompts) to generate output similar to human-generated content. In practice, this output frequently takes the form of text and images (Romero et al., 2024). Rudolph et al. (2023) posit the existence of three categories of AI tools: teacher-facing, system-facing, and student-facing. These systems mostly employ some sort of Natural Language Processing (NLP) or Natural Language Production, which describes the ability of a system to process not only prepared and refined data but also language in the way a human user would naturally use it (Chowdhary, 2020). Examples of NLP-based AI tools commonly used in higher education include:

- Translation tools: Machine translation tools receive written text as input and provide translated text through neural methods in a selected language (Polakova & Klimova, 2023; Stahlberg, 2020).
- Paraphrasing tools: These systems, which often use similar techniques as neural machine translation, provide alternative formulations of written words or text segments (Rogerson & McCarthy, 2017).
- Summarizing tools: Automatic text summarization refers to eliciting the key relevant information of a piece of text and returning it as a compressed version (El-Kassas et al., 2021).
- Generative tools: Generative systems use methods that produce content independently after being provided input in the form of prompts (Lim et al., 2023).

Assessment and goal orientation

Assessment is a factor that should act as a stimulus for student learning (Fischer et al., 2024). In this regard, the literature has often dwelt on the relationship between these two key processes in training and education; in fact, learning and assessment are linked and closely connected. It is from the relationship between these two processes that metacognitive awareness arises, enabling the learner to engage in critical and constructive thinking. Assessment, in particular, has or should have a fundamental role in helping institutions to create effective learning systems, teachers to structure learning content in a functional way and in developing among students the ability to make evaluative judgements about their learning, their work and that of others. Assessment is understood as the systematic gathering of students' information to draw inferences about their learning process (Baker et al., 2016). It can be classified according to the mode, format, and type chosen in the assessment design (Heil & Ifenthaler, 2023). The mode can include teacher, automated, self, and peer assessment. The format may be diagnostic, formative or summative, and the type can be chosen from a broad range of tasks such as essays, quizzes, or project work. The design of assessment is important, as it profoundly influences the design of learning processes (Martin et al., 2019) and fulfils an important role in our education systems as a means of differentiation and certification, but also as part of the learning process to support students (Black & Wiliam, 2018). especially formative assessment can support students by receiving continuous feedback, fostering engagement and addressing the individual needs of learners (Gikandi et al., 2011). The connection between learning, assessment and goal orientation is highly influential. For this reason, one cannot talk about learning and assessment without confronting the goals one intends to achieve and the means one plans to employ and use to achieve the goals one intends to pursue. What is the goal, what means is most appropriate to achieve my goal optimally, how much time do I have, what resources can I use, and what are my competences? These are all questions anyone with a goal asks or should ask.

Various models and theories on goal achievement are proposed in the literature. The theory of achievement goal orientation differentiates between two overarching types: performance orientation and learning orientation. According to the theory, learners who pursue performance goals tend to be motivated by their evaluation and being judged competent, while pursuing learning goals might stem from the motivation to improve their abilities (Dweck & Leggett, 1988). The appropriate and motivating use of AI tools can be a contextual element in supporting student academic success, promoting students' retention and avoiding possible drop-out situations (Chiu et al., 2023). In the context of online learning, individual goal orientation significantly influences students' behaviour (Adesope et al., 2015) as well as their preferences in learning analytics (Schumacher & Ifenthaler, 2018b). The distinction between performance and goal orientation is also linked to the broader picture we have of assessment and education and the distinction between seeing assessment as a way of certifying and classifying students or as a tool for encouraging reflection, providing feedback, and improving learning (Urdan & Kaplan, 2020). Guided by this thought and the public discourse surrounding the availability of AI for students in education, a new challenge emerges in investigating how GenAI tools can be used in different strategies of learners by either supporting them in fostering their learning in the process of assessment or allowing for them be judged competently by an assessor. The positive use of such tools can also be a useful element for the student's future, in fact, knowing about and knowing how to use AI and GenAI tools in the education context can be useful for students' career orientation and in the life-long learning process (Poquet & de Laat, 2021; Yupelmi et al., 2024).

Generative artificial intelligence for assessment

A specific use case of GenAI in education lies in different assessment scenarios, with the public discourse, as well as the research on this topic, tending to focus on a potential disruptive potential of GenAI or a way to catalyse change (Jensen et al., 2024). Concerns include critical discussion about privacy and ethics as well as potential biases (Mao et al., 2024) but focus mostly on the integrity of assessment (Cotton et al., 2024). This is further reflected in the GenAI policies of universities, which predominantly focus on the originality of student work. (Luo, 2024). At the same time, the possibilities of GenAI in assessment go far beyond utilising it for mere generation of content (Lim et al., 2023). Online assessment, especially supported by GenAI, may take on different pedagogical functions as part of online learning environments, for example, through scaffolding or adaptive learning (Webb & Ifenthaler, 2018).

Ansari et al. (2024) conducted a systematic scoping review with $N=69$ studies of higher education literature regarding using GenAI in the form of ChatGPT. They emphasised the importance of ensuring that teachers are designing assessment tasks that require critical thinking and human intelligence, as well as helping their students to develop AI literacy. A scoping review with $N=32$ empirical studies by Xia et al. (2024) regarding the transformation of assessment through GenAI furthermore emphasizes the need for more AI literacy as well as more diverse assessment methods and a re-thinking of assessment policies.

Research gap and study objectives

Research considering the transformation that GenAI can have on HE assessment encompasses the integrity of assessment (Cotton et al., 2024), while simultaneously opening up potential for additional assessment possibilities such as authentic assessment, adaptivity or automated feedback (Mao et al., 2024). Additionally, there is a clear call for more AI competence for all stakeholders (Xia et al., 2024; Ansari et al., 2023). The need to develop GenAI tools that are both user-friendly and congruent with educational objectives is imperative to facilitate their integration and enhance their efficacy in promoting student learning and assessment (Zhou et al., 2024).In this polarized discussion, this study aims to create a more nuanced understanding of GenAI in learning and assessment in relation to the individual students' AI competencies, needs and expectations, as well as their actual intended use of different GenAI tools in their learning and assessment processes. Therefore, this study not only aims to discuss potential chances and pitfalls of GenAI in learning and assessment but also expands the current literature through a cross-cultural analysis of individuals' dispositions as well as a nuanced analysis of AI competence as a multi-faceted construct. Furthermore, most studies focus on ChatGPT as the singular tool that students might use. To achieve a comprehensive overview as well as investigate the manifold use cases of AI, a broad view of tools is taken to encompass relevant and specific application scenarios of GenAI tools in assessment as well as students' evaluation of these.

This international study aims to investigate the perception of students of AI competence rather than the impact of different GenAI tools in the context of learning and assessment. Given previous assumptions (Dai et al., 2023; Kim et al., 2021), it is hypothesised that students' AI competence varies across specific dimensions (Hypothesis 1a) and that students from different countries exhibit comparable levels of AI competence (Hypothesis 1b).

Further, we assume that GenAI tools in the context of HEIs are perceived differently concerning their expected support for learning and assessment (Hypothesis 2). The students' AI competence is expected to significantly influence the evaluation of the tools for learning and assessment support concerning the overall rating of the AI tools (Delcker et al., 2024) (Hypothesis 3).

Based upon the results of these hypotheses, another exploratory approach is taken to investigate students' intent to use different AI tools for application in assessment scenarios in higher education. We assume that students perceive different usage benefits for each GenAI tool (Hypothesis 4) and attribute different supporting factors to aiding the pursuit of learning or performance goals (Adesope et al., 2015; Schumacher & Ifenthaler, 2018b). This will be investigated through latent factor analysis and confirmatory factor analysis.

Method

Participants and sampling

The research was undertaken via an online survey, and a convenience sampling method was applied by approaching students in HE classes, providing them with the link, and asking them to complete the survey. The results were collected from a total of $N = 223$ students from one Australian (35.43%), one German (36.77%), and one Italian (27.80%) university. The average age of the participants was 24 years ($SD = 7.61$), with 22.42% of the students identifying as male, 76.23% as female, and 1.34% as non-binary. Most students (82.06%) studied at the undergraduate level. Ethics approval was obtained for this research at the participating universities.

Instrument

The survey used standardized items modified from previous instruments around the following themes: Student assessment practices and student beliefs about assessment methods, student understanding of AI, and student competence in using AI. All items were designed as statements with closed answers following a 4-point Likert scale (1 = do not agree to 4 = fully agree).

In the first section of the survey, participants completed the questionnaires based on Gibbs and Dunbar-Goddet (2007) and Pereira et al. (2017) concerning individual learning and assessment experience (15 items; Cronbach's $\alpha = 0.64$).

In the second section, participants were presented with a series of videos showcasing various AI tools. They were then invited to share their perceptions regarding a range of factors, including the learning potential, the applicability of these tools in achieving specific goals, their acceptability, and considerations related to privacy, through an adapted version of a survey by Schumacher and Ifenthaler (2018a) (15 items per tool, Cronbach's $\alpha = 0.93$).

In the third and last section, participants' general AI competence was assessed through a modular survey by Delcker et al. (2024) covering different dimensions of AI competence, with the selected sub-categories for this context being theory, laws and regulations, the impact of AI, and attitudes towards AI (18 items; Cronbachs' $\alpha = 0.84$).

Materials

Participants were presented with a video introducing a GenAI tool in a specific use case related to higher education. All videos were structured similarly, commencing with a problem that was already familiar to the participants and the specific use case of the GenAI tool. For instance, in the case of ExplainPaper, the narrator explains their personal difficulty in reading complex texts for an essay assignment and the time required to look up highly specific and technical terms. The tool is then demonstrated in action through a screencast, which introduces the functionalities and shows how the narrator solved their problem using the GenAI tool. A total of six GenAI tools were included in this study:

1. ChatGPT (https://chat.openai.com/) is a large language model (LLM)-based chatbot developed by OpenAI. It uses its training on a large dataset of text and code to engage in conversational-style interactions. ChatGPT provides answers in a conversation format upon prompts given through the users by generating text, translating languages, writing various types of creative content, and answering questions in an informative manner.
2. DeepL (https://www.deepl.com/translator) is a machine translation tool that utilizes deep learning algorithms to deliver translations between multiple languages. It offers two main functionalities: direct text input for on-the-fly translation and file upload for translating entire documents. This capability caters for users with different translation needs, from short phrases to large documents. Users also can change the tone of voice to 'formal' or 'informal.'

3. ExplainPaper (https://www.explainpaper.com/) is a research paper comprehension tool. It uses a large language model (LLM) to improve user understanding of complex scientific concepts. It provides two main functionalities: an explanation functionality and a chatbot functionality. The explanation functionality allows users to upload a research paper (in PDF format) or paste a link to it. ExplainPaper then uses its LLM to generate a simplified explanation of the paper's content, potentially including a gist or a more detailed outline (depending on the subscription plan chosen). In addition, the chatbot function allows users to highlight specific terms or passages within the uploaded paper. ExplainPaper's LLM then acts as a virtual reading companion, providing clear explanations for the highlighted elements and fostering a more interactive and engaging reading experience.
4. PaperDigest (https://www.paper-digest.com/) helps streamline scientific literature reviews. It goes beyond simple summarisation by offering a range of functionalities to improve research efficiency. A key feature is the ability to summarise research articles. Users can enter a DOI or upload a PDF, and PaperDigest extracts the paper's key points, providing a concise overview of the research and its key findings.
5. Quillbot (https://quillbot.com/) is a multifaceted writing tool that includes paraphrasing as a core feature. It is aimed at users who want to improve the clarity, conciseness and overall quality of their writing. Beyond basic paraphrasing, Quillbot offers different modes, such as 'Fluency' and 'Formal', to tailor the paraphrased text to a specific tone or style. This versatility allows users to achieve their desired writing results, whether simplifying complex sentences, replacing synonyms or maintaining a formal register.
6. Tome (https://tome.app/) helps to simplify the creation of presentations. Users provide a text prompt outlining the desired presentation topic. Tome then generates a first multimedia draft with content, images, and potentially different slide layouts. This approach allows users to focus on refining the core message and content while Tome does the initial work of gathering information, visual design and structure.

These tools were explicitly selected as they allow for usage in many scenarios, encompassing the broad range that GenAI in online assessment can have, including translation, summarizing, paraphrasing and generation of content (Delcker et al., 2024). Furthermore, while they all implement some form of GenAI, they have different functionalities and use case scenarios. By investigating these tools, this research, on the one hand allows for a comprehensive overview of GenAI in assessment as well as a nuanced differentiation of different application scenarios. By collecting data about different tools, we aimed to understand better GenAI use and preferences among participating students.

Procedure and data analysis

A data collection protocol was created to ensure a similar data collection process for all three participating HEIs. An online platform was put into place, along with information about data privacy and ethics, as well as a cover letter detailing the extent of the research. The data collection tools were shown following brief one-minute video clips that demonstrated possible use cases for each of the following GenAI tools by students—ChatGPT, DeepL, ExplainPaper, PaperDigest, Quillbot, and Tome. Lastly, the participants provided their demographic data, including their study course, gender (male, female, or non-binary), and age (number of years). The process of gathering data took about 45 min. During storage and analysis, all data were anonymised under standard research data protection procedures. The data were cleaned and combined for descriptive and inferential statistics using R statistics version 4.3.0. All effects were tested at the 0.05 significance level, and effect size measures were computed where relevant.

Results

Students AI' competence

Concerning hypothesis 1a, ANOVA revealed significant differences in dimensions of AI competence, $F(3, 891) = 48.33$, $p < 0.001$, $\eta 2 = 0.140$. Tukey-HSD test discovered significant differences for the four dimensions, i.e., the highest AI competence dimension attitude ($M = 3.16$; $SD = 0.49$) differed significantly from the dimension impact ($M = 2.95$; $SD = 0.51$), regulations ($M = 2.81$; $SD = 0.62$), and the lowest AI competence dimension theory ($M = 2.58$; $SD = 0.47$), $p < 0.001$ (see Table 1). Further pairwise comparisons revealed significant differences between all AI competence dimensions.

Thus, Hypothesis 1a is accepted, indicating that the dimensions of AI competence vary considerably.

Regarding hypothesis 1b, ANOVA indicated no significant difference in AI competence between students from the three participating HEIs, $F(2, 222) = 2.49$, $p > 0.05$, $\eta 2 = 0.022$ (see Table 1).

Therefore, hypothesis 1b is accepted, with students from different countries exhibiting comparable levels of AI competence.

Expected support for learning dependent on tools

Concerning hypothesis 2, ANOVA revealed significant differences in expected support for learning and assessment between the six GenAI tools (ChatGPT, DeepL, ExplainPaper, PaperDigest, Quillbot, Tome), $F(5, 1337) = 29.51$, $p < 0.001$, $\eta 2 = 0.100$. Tukey-HSD test suggests significant differences for the highest rated AI tool ExplainPaper ($M = 3.07$; $SD = 0.54$) and ChatGPT ($M = 2.69$; $SD = 0.55$), Quillbot ($M = 2.63$; $SD = 0.61$), Tome ($M = 2.51$; $SD = 0.68$), $p < 0.001$ (see Table 2).

Hypothesis 2 is, therefore, accepted. This indicates that the expected support of GenAI tools for learning and assessment is perceived differently.

Table 1 Means (standard deviations in parentheses) of artificial intelligence competence dimensions across the higher education institutions (N = 223)

	Artificial intelligence competence dimensions			
	AI Theory	**AI Regulations**	**AI Impact**	**AI Attitudes**
AUS	2.56 (.49)	2.85 (.55)	3.01 (.49)	3.01 (.50)
GER	2.63 (.44)	2.79 (.66)	3.01 (.41)	3.27 (.48)
ITA	2.56 (.49)	2.81 (.64)	2.81 (.61)	3.21 (.60)
All	2.58 (.47)	2.81 (.62)	2.95 (.51)	3.16 (.49)

AUS australia; *GER* germany; *ITA* italy

Table 2 Means (standard deviations in parentheses) of AI tool's expected support for learning and assessment across the higher education institutions (N = 223)

	GenAI tool					
	Chat GPT	**DeepL**	**ExplainPaper**	**Paper Digest**	**Quillbot**	**Tome**
AUS	2.71 (.59)	2.81 (.69)	3.07 (.58)	2.96 (.61)	2.58 (.65)	2.49 (.70)
GER	2.62 (.50)	3.05 (.63)	3.07 (.54)	3.00 (.59)	2.65 (.60)	2.48 (.70)
ITA	2.74 (.56)	3.06 (.57)	3.05 (.51)	2.86 (.58)	2.69 (.58)	2.58 (.64)
All	2.69 (.55)	2.97 (.64)	3.07 (.54)	2.95 (.60)	2.63 (.61)	2.51 (.68)

AUS australia; *GER* germany; *ITA* italy

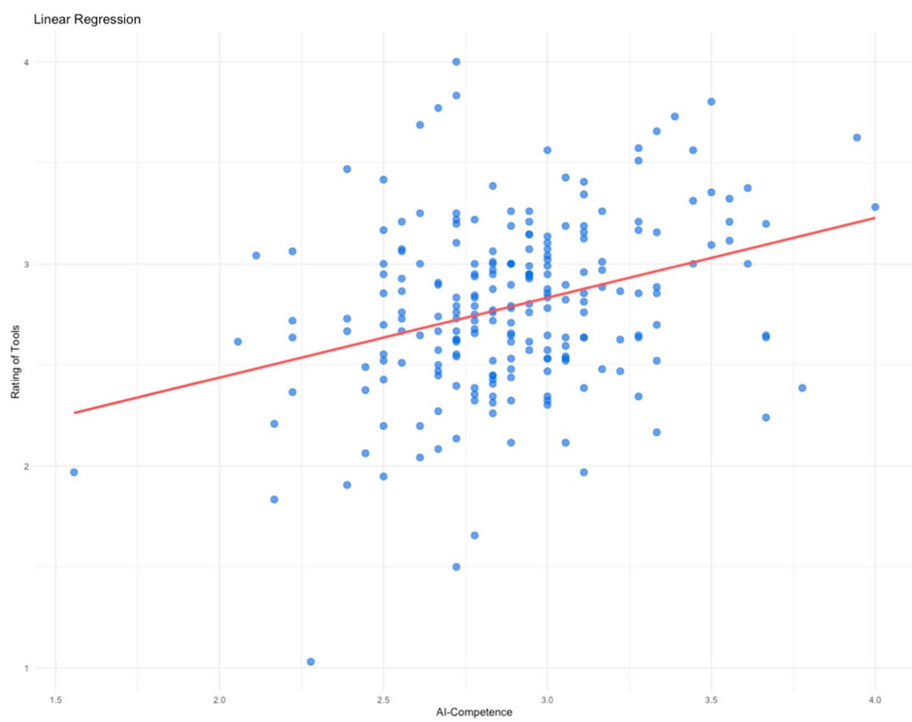

Fig. 1 Influence of AI competence on the rating of tools

Influence of AI competence

A weak positive correlation could be found between the self-reported AI competence of the students and their average evaluation of the GenAI tools, $r = 0.32$, $p < 0.01$. A linear regression was conducted to analyse the relation between students' AI competence and their rating of AI-tools (see Fig. 1). The level of AI competence significantly predicts the students' rating of the GenAI tools $\beta = 0.32$. The AI competence did explain a small but significant variance in the rating of the tools $R^2 = 0.1$, $F(1, 221) = 25.34$, $p < 0.01$.

Therefore, hypothesis 3 is accepted, with the level of self-reported AI competence influencing the overall expected support of GenAI tools for learning.

Analysis of specific benefits of tools

A confirmatory factor analysis was conducted to confirm that the items used in this study relate to the assumed latent factors aiding learning or reaching a performance goal. The average ratings across all AI tools were used in this analysis. The items used for relating to learning goals are 1.: 'If I used the AI tool shown in the video, I would gain a better understanding of the learning content', 2.: 'If I used the AI tool shown in the video, I would be able to analyse my learning results, 3.: 'Using the AI tool shown in the video would help me to achieve my learning goals'. For assessing performance goals: 1. 'If I used the AI tool shown in the video, I would achieve greater learning success', 2. 'If I used the AI tool shown in the video, I would optimize my learning process', 3.: 'If I used the AI tool shown in the video, I would get better grades.'

The model shows a good fit. $CFI = 0.977$, $TLI = 0.956$, $SRMR = 0.028$, $RMSEA = 0.128$, according to the cut-off values postulated by Hu and Bentler (1999), which call for a CFI and TLI higher than 0.95 and an SRMR lower than 0.08. only the RMSEA is higher than the expected 0.06 (see Fig. 2).

Accordingly, students were asked about their agreement with the specific impacts of the tools in their assessment processes. Concerning Tome, the highest agreement was found in the possibility of supporting the students in receiving better grades ($M = 2.94$, $SD = 0.79$) as well as for Quillbot ($M = 3.02$, $SD = 0.76$). ChatGPT's highest-rated possible support was found in optimizing the learning process ($M = 2.92$, $SD = 0.7$). The most highly valued component of DeepL was its assistance in understanding the learning content, ($M = 3.24$, $SD = 0.77$), which was also the highest for ExplainPaper ($M = 3.39$, $SD = 0.62$), and PaperDigest ($M = 3.14$, $SD = 0.71$). Following the highest perceived benefits as well as the results of the confirmatory factor analysis and the significant influence of the AI competence on the rating of the tools, a structural equation model was applied to the data to investigate in how far the tools can be grouped by an underlying factor

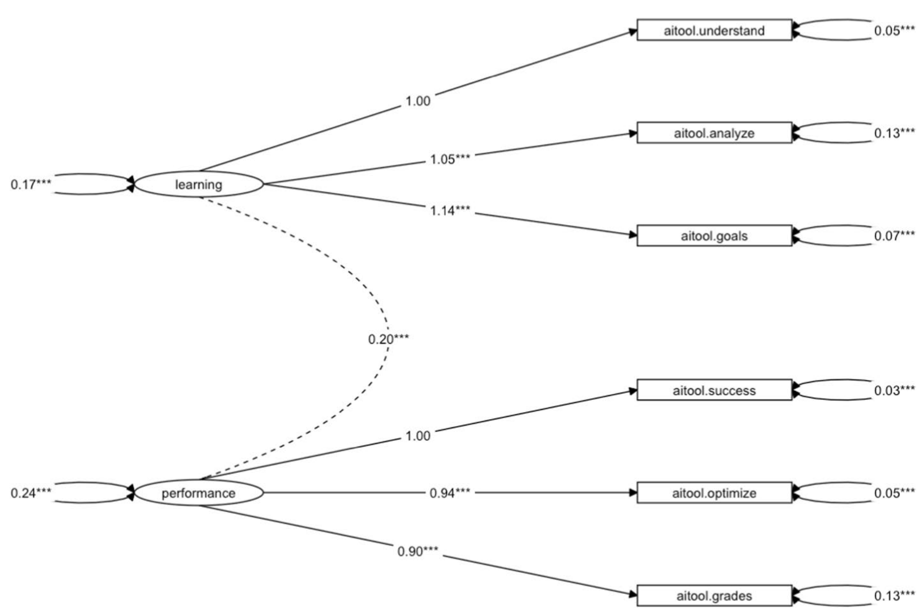

Fig. 2 Confirmatory factor analysis of items

based upon sharing the benefits identified and how far this is influenced by individual AI competence. They were grouped depending on how well the tools were rated on the scales, indicating support for performance or learning goals (see Fig. 3).

This model assumes that the tools with similar highest-rated aspects can be grouped in the overall evaluation by the students. Furthermore, this model assumes that the individual AI competence highly influences these latent factors in this context. The model has a good fit. $CFI = 0.96$, $TLI = 0.931$, $SRMR = 0.044$, $RMSEA = 0.104$.

Therefore, Hypothesis 4 is accepted, with ChatGPT, Tome and Quillbot being used for reaching performance goals and PaperDigest, DeepL and ExplainPaper for learning goals.

Discussion

Simply encountering AI and GenAI in the context of HEIs learning and assessment is not enough. Kasneci et al. (2023) emphasize that GenAI holds great promise for enriching student learning and teacher support but requires careful integration that addresses potential bias, privacy, security and ethical concerns, as well as ongoing human oversight and development of critical thinking. Thus, this international survey study investigated AI competence and students' perceptions of GenAI tool support in the context of HEIs learning and assessment. It underscores the importance of fostering a multifaceted understanding of GenAI in HEIs learning and assessment.

The findings support our first hypothesis (1a), revealing significant differences across the four dimensions of AI competence (theory, regulations, impact and attitude) (Delcker et al., 2024). Interestingly, the students showed the strongest AI competence in the 'attitude' dimension. This reflects a positive perception and enthusiasm for AI, i.e., students are generally receptive to the potential of AI and its integration into various aspects of their academic experience (Chan & Hu, 2023; Stöhr et al., 2024). This enthusiasm could be due to several factors: Students may be drawn to the innovative nature of AI and its ability to transform learning methods, access to information or even communication in educational settings (Almulla, 2024). In addition, positive portrayals of AI in the media as a powerful tool for problem-solving and progress could have contributed to students' enthusiasm (Rodway & Schepman, 2023).

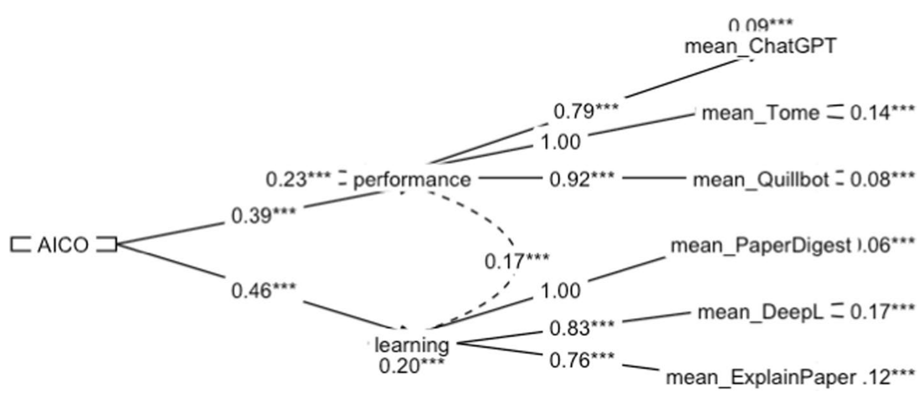

Fig. 3 Structural equation model

However, it is important to recognise that enthusiasm alone does not equate to a comprehensive understanding of AI. Furthermore, these findings highlight a potential need to bridge the gap between students' enthusiasm and their understanding of technical aspects, laws and regulations, as well as limitations of AI technologies. This is consistent with another important finding of this study, namely that students who report a higher AI competence also evaluate the support of AI for teaching and learning higher (Hypothesis 3), suggesting a need for providing students greater assistance in building AI competence to avoid generating an imbalance among them (Delcker et al., 2024). In addition, there were no significant differences in overall AI competence between students from the three participating countries, supporting hypothesis 1b. This suggests that students from the three participating countries demonstrated comparable levels of AI competence despite potential differences in their HEIs or differences in their exposure to AI technologies. Accordingly, the globalised nature of AI access in the participating countries might play a role. Students could gain exposure to similar information and perspectives on AI through online resources, social media, or international educational platforms. In addition, the increasing prominence of AI in popular culture and media may contribute to a more consistent level of general awareness of AI across geographical boundaries (Hsu & Ching, 2023). Furthermore, the specific dimensions of AI competence measured in this study (theory, regulation, impact and attitude) may transcend national contexts and reflect broader trends in how students approach new technologies.

Our second hypothesis (2) regarding GenAI tool support was also confirmed. Students perceived ExplainPaper, a tool that aids comprehension of scientific papers, as the most supportive for learning and assessment. This suggests a preference for tools that directly enhance understanding and critical thinking over those focused on content generation or paraphrasing (ChatGPT, Quillbot) or translation (DeepL). Interestingly, Tome, a tool that generates presentation slides based on prompts, received the lowest expected support rating. Rather than relying solely on AI-generated content, this preference for comprehension-focused tools such as ExplainPaper may indicate students' desire to engage with complex information and form their own arguments. Effective presentations often depend on the presenter's ability to analyse information critically, synthesise key points and construct a compelling narrative (Jonassen, 2010). Tools such as ExplainPaper can support this process by facilitating the understanding of source material. However, AI-generated presentation slides, such as those offered by Tome, pose a risk in reducing students' engagement with the content and hindering the development of the critical thinking skills needed to construct strong arguments (Spector & Ma, 2019). In line with this concern, it is even more important to investigate the advantages the students noticed with the specialized instruments for their learning processes and the underlying latent factors identified by the structural equation model.

As hypothesis 4 is accepted, students see the different tools as beneficial for different purposes in higher education. ExplainPaper, PaperDigest, and DeepL were considered helpful in assisting comprehension and highly correlated with each other in the overall rating. Tome and Quillbot were perceived as providing the most value in helping the students get better grades. ChatGPT, on the other hand, was estimated to help optimize the learning process. The structural equation model revealed that these three tools were highly correlated and loading to the same latent factor. These could indicate different possible applications to support different achievement orientations. Therefore, when researching the impact of AI tools on student learning, it is critical to distinguish between different types of AI tools as well as distinct features of generative AI and its use in the context of education. Furthermore, students' motivational dispositions are crucial in interacting with online learning tools (Schumacher & Ifenthaler, 2018b).

These results can create the basis for larger discussions on how we see students' usage of AI in assessment and what stakeholders in higher education want from assessment. This concerns the concept and expectations of individual goal orientation and the broader assumptions behind examining students (Urdan & Kaplan, 2020). When discussing the threat of students' cheating by using AI, we should consider how we view assessment and our assumptions about assessment and student motivation. If the discussion focuses on the fear of tools primarily designed to improve performance rather than students' focus on tools used to improve learning and understanding, we need to consider the different functions that assessment can have beyond certification to support learning (Black & William, 2018).

Overall, the discussion on AI tools in assessment must be conducted broadly and deeply and include students' perceptions and evaluations. This study highlights the uneven development of AI competence among students, with a positive attitude exceeding theoretical understanding. Additionally, students seem to value GenAI tools that support comprehension and critical thinking over those focused solely on content creation. Future research could explore tailored interventions to enhance students' understanding of AI theory and regulations while investigating how GenAI tools can be effectively integrated into learning activities to promote deeper learning and critical thinking skills. The research results suggest that it is important to consider particular GenAI tools rather than grouping all GenAI tools together.

Implications

Various implications can be taken from this study's findings that could help advance psychological reflections and pedagogical practices in navigating these emerging frontiers in HEIs. The most striking finding is the disparity across the four dimensions of AI competence. While students have a positive attitude towards AI, their understanding of the underlying theory remains lower. This highlights the need for educational interventions that bridge the gap between enthusiasm and technical knowledge (Stein et al., 2024) and also between AI and GenAI use and digital competences (Svoboda, 2024). Curricula can be designed to integrate fundamental concepts of AI with practical applications, fostering a more nuanced understanding of this rapidly evolving field (Aler Tubella et al., 2024). These results form the basis for both practical educational actions as well as for research. In the future, it should take on a more nuanced examination and utilisation of AI competence, considering the differences between the dimensions and reflecting individuals' dispositions. Further, the study reveals a student preference for GenAI tools that support comprehension and critical thinking over those focused solely on content generation or translation (Janse van Rensburg, 2024). ExplainPaper, a tool aiding scientific paper understanding, received the highest expected support rating. This suggests that students value tools that enhance their ability to engage with complex information and develop critical analysis skills (Jonassen, 2010; Spector & Ma, 2019). Incorporating such tools into learning activities can encourage deeper engagement with course material and promote independent learning. However, while students perceive some GenAI tools as valuable, the relatively low expected support for GenAI tools like Tome, which generate presentation slides, suggests a need for a balanced pedagogical approach. GenAI tools should complement, not replace, the development of core academic competence (Mah & Ifenthaler, 2017, 2018). Pedagogical strategies should integrate GenAI tools thoughtfully, ensuring students develop critical thinking and the ability to construct arguments independently (Walter, 2024). Regarding scientific research, the different appreciation of the tools, as well as the different application scenarios, should be investigated systematically. The opportunities and applications of the specific applications need to be investigated in detail and connected with the research on opportunities for transformation of assessment through GenAI (Xia et al., 2024).

Limitations and outlook

This study is not without limitations. Firstly, the findings may not apply to the general population of higher education students as they were based on convenience sampling from three participating universities, which may limit external validity (Campbell & Stanley, 1963).

Secondly, while the instruments adopted have been previously tested for reliability and validity (Delcker et al., 2024; Gibbs & Dunbar-Goddet, 2007; Pereira et al., 2017), further external criterion and mixed methods designs may provide more robust empirical insights into students' AI competence and related preference of GenAI tools for supporting learning and assessment. Accordingly, our current research is expanding to include samples from additional countries and adding a qualitative investigation focusing on students' and teachers' perceptions of AI competence and the pedagogical practices related to GenAI tools. Also, the level of school digitization reached by countries that have participated and will participate in future studies should be considered.

Thirdly, the students did not interact with the GenAI tools but were shown a screencast demonstrating the potential use of GenAI for their learning and assessment. This could impact the transferability from perception to performance. The study only provided insights into students' intent and did not include an actual experiment or use-case study.

In the future, it will be important to investigate if the ethical evaluation is a hindrance for students not to use the tools in actual practice. Furthermore, students' goal orientation should be connected to the different tools' usage and hypothesized purpose (Adesope et al., 2015). Therefore, AI research in HEIs should be further developed towards longitudinal research designs to investigate possible developments in AI competence. Such designs could include different learning and assessment situations using different GenAI tools. Tracking the potential development of AI competence over time and investigating the effectiveness of interventions would further contribute to the practical implications of GenAI in higher education.

In conclusion, while AI offers significant potential for higher education institutions, ethical considerations and responsible use are paramount. To promote digital education and to successfully integrate AI, universities must upskill educators, adapt teaching models, equip students with relevant skills, keep problematic technology use under control (e.g., smartphone overuse and addiction) and establish ethical guidelines for AI use (Karam, 2023). This proactive approach will ensure that AI is used effectively and ethically, driving positive change in higher education.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Author contributions
All authors participated in planning the study, designing the data collection tools, collecting and analysing data for the study. The first author and corresponding author led the writing up process, with contributions from the third, fourth, fifth, and sixth authors. All authors read and approved the final manuscript.

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Declarations

Informed consent
Informed consent was obtained by the participating institutions.

Ethical approval
All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Competing interests
The authors declare no known competing financial or non-financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors declare no conflict of interest.

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