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Navigating the Terrain:

Emerging Frontiers in Learning Spaces, Pedagogies, and Technologies

Demystifying the Power of Generative Artificial Intelligence Tools in Higher Education: International Students' Perspectives

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Artificial intelligence represents an emerging frontier for higher education institutions, potentially personalising learning, automating tasks, and supporting student outcomes. This study examines international students' perceptions of the recent proliferation of generative artificial intelligence tools in the context of academic learning and assessment. The study involved N = 223 students from three different higher education institutions located in Australia, Germany and Italy. The focus was on the student's competence in artificial intelligence and their perception of six different generative artificial intelligence tools concerning learning and assessment. The findings suggest that the dimensions of competence in artificial intelligence vary considerably and that students from different countries have a comparable level of competence in artificial intelligence. Further findings indicate that the expected support of generative artificial intelligence tools for learning and assessment is perceived differently. This study highlights the need for increased pedagogical attention to artificial intelligence, bridging the gap between students' enthusiasm and technical knowledge. It suggests that effective integration of generative artificial intelligence tools should also prioritise the development of critical thinking and comprehension skills over content generation.

Keywords: higher education, generative artificial intelligence, tools, assessment, student perspective, international perspective

Introduction

The rapid advances in artificial intelligence (AI) are continuously transforming the higher education sector. For instance, predictive analytics are optimising resource allocation (Gibson & Ifenthaler, 2020) and improving student success rates (Ifenthaler & Yau, 2020), or adaptive assessment systems are empowering students to monitor their learning processes (Ifenthaler & Sahin, 2023). Hence, AI has the potential to personalise learning experiences, automate administrative tasks, and analyse vast datasets to improve student outcomes (Bond et al., 2024). This confluence of factors positions AI as an emerging frontier in higher education, poised to reshape how current and future generations learn and teach in higher education institutions (HEIs).

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 diverse ways (Zawacki-Richter et al., 2019). Accordingly, the presence of AI across HEIs necessitates a dynamic interplay between stakeholders and systems (Daugherty & Wilson, 2018; Ifenthaler & Schumacher, 2023). This engagement is crucial for fostering the development of AI competence – the ability to comprehend, utilise, and critically evaluate AI tools (Kim et al., 2021). AI competence 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 process (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).

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 universities, with some viewing it as a beneficial tool and others expressing concern about its potential impact on education (Mamo et al., 2024). Accordingly, the increasing sophistication of AI tools is blurring the lines between original scientific thought and AI-generated content, posing significant challenges to maintaining academic integrity (Maral, 2024). 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). However, questions remain unanswered about how students use GenAI and their views on 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 student AI competence and their perceptions of GenAI tools in the context of learning and assessment within HEIs.

Background

Artificial intelligence competence

The existing literature on AI competence identifies different skills, which can be summarised in distinctive competence dimensions. For instance, AI competence involves a basic understanding of the functionality of AI (Attwell et al., 2020), including identifying whether 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 educational data (Papamitsiou et al., 2021). This emphasises identifying AI's potential and risks in education, society, and the workplace (Attwell et al., 2020). 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 for the ethical implementation of AI. Sanusi et al. (2022) adopt 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 professionalisation as the cornerstone of a competent approach to AI. This framework is designed modularly and can be adapted according to the target group.

Generative artificial intelligence tools

The end of 2022 saw a rapid increase in the number and variety of available tools utilising GenAI. 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, namely teacher-facing, system-facing, and student-facing tools. 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 (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).
- Summarising tools: Automatic text summarisation refers to eliciting the key relevant information of a text and returning it as a compressed version of the text (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).

Research aims

This international study aims to investigate higher education students' competence related to AI and their perception of 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).

Method

Participants and context

The research was undertaken via an online survey with a convenience sample 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 identified 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 standardised items modified from previous instruments around the following themes: Student assessment practices, student beliefs about assessment methods, student understanding of GenAI, and student competence in using GenAI. All items were designed as statements with closed answers following a 4-point Likert scale (1 = do not agree to 4 = fully agree).

Based on the questionnaires by Gibbs and Dunbar-Goddet (2007) and Pereira et al. (2017), a first sub-section of the survey was created concerning individual learning and assessment experience (15 items; Cronbach's α = .64). Example item for section one: 'I study regularly for assessments'. In the second section of the survey, 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 potential for learning, 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 (2018) (15 items per tool, Cronbach's α = .93). Example item for section two: 'If I used the AI tool shown in the video, I would achieve greater learning success'. In addition, students' 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' α = .84). Example item for section three: 'I am able to evaluate the credibility of results which stem from AI-based systems'.

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.

- 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. Users provide prompts or questions, and ChatGPT responds in a human-like manner by generating text, translating languages, writing various types of creative content, and answering questions in an informative manner.
- 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.
- 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.
- 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.
- 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.
- Tome (https://tome.app/) helps 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.

Procedure and data analysis

A data collection protocol was developed for the three participating HEIs to guarantee a comparable data collection procedure. An online platform was implemented, which included a cover letter outlining the scope of the research and information about data privacy and ethics. The data collection instruments were presented following short video clips (one minute in length) illustrating potential ways students might use each of the following GenAI tools: ChatGPT, DeepL, ExplainPaper, PaperDigest, Quillbot, and Tome. Finally, participants stated demographic information such as age (number in years), gender (male, female, non-binary), and study course. Data collection took approximately 45 minutes.

Following standard research data protection practice, all data were stored and analysed anonymously. The data were cleaned and combined for descriptive and inferential statistics using R statistics version 4.3.0. All effects were tested at the .05 significance level, and effect size measures were computed where relevant.

Results

Concerning hypothesis 1a, ANOVA revealed significant differences in dimensions of AI competence, $F(3, 891) = 48.33$, $p < .001$, $\eta 2 = .140$ (moderate effect). Tukey-HSD test discovered significant differences for the four dimensions, i.e., the highest AI competence dimension attitude ($M = 3.16$; $SD = .49$) differed significantly from the dimension impact ($M = 2.95$; $SD = .51$), regulations ($M = 2.81$; $SD = .62$), and the lowest AI competence dimension theory ($M = 2.58$; $SD = .47$), $p < .001$ (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.

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)

Note. AUS = Australia; GER = Germany; ITA = Italy

Regarding hypothesis 1b, ANOVA indicated no significant difference in AI competence between students from the three participating HEI, $F(2, 222) = 2.49$, $p > .05$, $\eta 2 = .022$ (small effect) (see Table 1). Therefore, hypothesis 1b is accepted, with students from different countries exhibiting comparable levels of AI competence.

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), $F(5, 1337) = 29.51$, $p < .001$, $\eta 2 = .100$ (moderate effect). Tukey-HSD test suggests significant differences for the highest rated AI tool ExplainPaper ($M = 3.07$; $SD = .54$) and ChatGPT ($M = 2.69$; $SD = .55$), Quillbot ($M = 2.63$; $SD = .61$), Tome ($M = 2.51$; $SD = .68$), $p < .001$ (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 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					
	ChatGPT	DeepL	ExplainPaper	PaperDigest	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)

Note. AUS = Australia; GER = Germany; ITA = Italy

Discussion

Simply encountering AI in the context of university learning and assessment is not enough. Kasneci et al. (2023) emphasise 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 university learning and assessment. It underscores the importance of fostering a multifaceted understanding of GenAI in HEI learning and assessment.

Findings

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 (Stöhr et al., 2024). This enthusiasm could be due to a number of 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). However, it is important to recognise that enthusiasm alone does not equate to a comprehensive understanding of AI. Our findings highlight a potential need to bridge the gap between students' enthusiasm and their understanding of the underlying technical aspects, laws and regulations, as well as limitations of AI technologies.

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 higher education systems or 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. (Delcker et al., 2024).

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. This preference for comprehension-focused tools such as ExplainPaper may indicate students' desire to engage with complex information and form their own arguments rather than relying solely on AI-generated content. 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, run the risk of reducing students' engagement with the content and hindering the development of the critical thinking skills needed to construct strong arguments (Spector & Ma, 2019).

Overall, the 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 or translation. 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.

Implications

Various implications can be taken from this study's findings that could help advance 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). 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). 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). Furthermore, in a recent Delphi study, Ifenthaler et al. (2024) identified strategies and actions for policymakers, researchers and practitioners, including privacy, ethics, algorithmic trustworthiness, fairness, equity, new stakeholder roles, human-AI collaboration, and the need for proactive policy development.

Limitations and future research

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. Thirdly, the students did not interact with the GenAI tools but were shown a screencast demonstrating the potential use of GenAI for their own learning and assessment. This could impact the transferability from perception to performance.

It is therefore suggested that AI research in HEIs should be further developed towards longitudinal research designs that can 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 successfully integrate AI, universities must upskill educators, adapt teaching models, equip students with relevant skills, 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.

References

Aler Tubella, A., Mora-Cantallops, M., & Nieves, J. C. (2024). How to teach responsible AI in Higher Education: challenges and opportunities. *Ethics and Information Technology*, *26*, 3. https://doi.org/10.1007/s10676-023-09733-7

Almulla, M. A. (2024). Investigating influencing factors of learning satisfaction in AI ChatGPT for research: University students perspective. *Heliyon*, *10*(11), e32220. https://doi.org/10.1016/j.heliyon.2024.e32220

Attwell, G., Bekiaridis, G., Deitmer, L., Perini, M., Roppertz, S., & Tutlys, V. (2020). *Artificial intelligence in policies, processes and practices of vocational education and training*. Institut Technik und Bildung (ITB). https://doi.org/10.26092/elib/307

Bhullar, P. S., Joshi, M., & Chugh, R. (2024). ChatGPT in higher education - a synthesis of the literature and a future research agenda. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-12723-x

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (2024). A meta systematic review of Artificial Intelligence in Higher Education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*, *21*, 4. https://doi.org/10.1186/s41239-023-00436-z

Chowdhary, K. R. (2020). *Fundamentals of artificial intelligence*. Springer. https://doi.org/10.1007/978-81-322-3972-7

Dai, Y., Liu, A., & Lim, C. P. (2023). Reconceptualizing ChatGPT and generative AI as a student-driven innovation in higher education. *Procedia CIRP*, *119*, 84–90. https://doi.org/10.1016/j.procir.2023.05.002

Daugherty, P. R., & Wilson, H. J. (2018). *Human + machine: Reimagining work in the age of AI*. Harvard Business Review Press.

Delcker, J., Heil, J., Ifenthaler, D., Seufert, S., & Spirgi, L. (2024). First-year students AI-competence as a predictor for intended and de facto use of AI-tools for supporting learning processes in higher education. *International Journal of Educational Technology in Higher Education*, *21*, 18. https://doi.org/10.1186/s41239-024-00452-7

El-Kassas, W. S., Salama, C. R., Rafea, A. A., & Mohamed, H. K. (2021). Automatic text summarization: A comprehensive survey. *Expert Systems with Applications*, *165*, 113679. https://doi.org/10.1016/j.eswa.2020.113679

Gibbs, G., & Dunbar-Goddet, H. (2007). The effects of programme assessment environments on student learning. *The Higher Education Academy*.

Gibson, D. C., & Ifenthaler, D. (2020). Adoption of learning analytics. In D. Ifenthaler & D. C. Gibson (Eds.), *Adoption of data analytics in higher education learning and teaching* (pp. 3–20). Springer. https://doi.org/10.1007/978-3-030-47392-1_1

Hsu, Y. C., & Ching, Y. H. (2023). Generative artificial intelligence in education, Part two: International perspectives. *TechTrends*. https://doi.org/10.1007/s11528-023-00913-2

Huang, X. (2021). Aims for cultivating students' key competencies based on artificial intelligence education in China. *Education and Information Technologies*, *26*(5), 5127–5147. https://doi.org/10.1007/s10639-021-10530-2

Ifenthaler, D., Majumdar, R., Gorissen, P., Judge, M., Mishra, S., Raffaghelli, J., & Shimada, A. (2024). Artificial intelligence in education: implications for policymakers, researchers, and practitioners. *Technology, Knowledge and Learning*. https://doi.org/10.1007/s10758-024-09747-0

Ifenthaler, D., & Sahin, M. (2023). Empowering higher education students to monitor their learning progress: opportunities of computerised classification testing. *Interactive Technology and Smart Education*, *20*(3), 350–366. https://doi.org/10.1108/ITSE-11-2022-0150

Ifenthaler, D., & Schumacher, C. (2023). Reciprocal issues of artificial and human intelligence in education. *Journal of Research on Technology in Education*, *55*(1), 1–6. https://doi.org/10.1080/15391523.2022.2154511

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: a systematic review. *Educational Technology Research and Development*, *68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

Janse van Rensburg, J. (2024). Artificial human thinking: ChatGPT's capacity to be a model for critical thinking when prompted with problem-based writing activities. *Discover Education*, *3*, 42. https://doi.org/10.1007/s44217-024-00113-x

Jonassen, D. H. (2010). Arguing to learn and learning to argue: design justifications and guidelines. *Educational Technology Research and Development*, *58*(4), 439-457. https://doi.org/10.1007/s11423-009-9143-8

Karam, J. (2023). Reforming higher education through AI. In N. Azoury & G. Yahchouchi (Eds.), *Governance in higher education* (pp. 275–306). Palgrave Macmillan. https://doi.org/10.1007/978-3-031-40586-0_12

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., . . . Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kim, S., Jang, Y., Kim, W., Choi, S., Jung, H., Kim, S., & Kim, H. (2021). Why and what to teach: AI curriculum for elementary school. In *Proceedings of the AAAI Conference on Artificial Intelligence, 35* (pp. 15569-15576). https://doi.org/10.1609/aaai.v35i17.17833

Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., & Pechenkina, E. (2023). Generative ai and the future of education: Ragnarök or reformation? a paradoxical perspective from management educators. *The International Journal of Management Education*, *21*(2), 100790. https://doi.org/10.1016/j.ijme.2023.100790

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727

Mah, D.-K., & Ifenthaler, D. (2017). Academic staff perspectives on first-year students' academic competencies. *Journal of Applied Research in Higher Education*, *9*(4), 630–640. https://doi.org/10.1108/JARHE-03-2017-0023

Mah, D.-K., & Ifenthaler, D. (2018). Students' perceptions toward academic competencies: the case of German first-year students. *Issues in Educational Research*, *28*(1), 120–137. http://www.iier.org.au/iier28/mah.pdf

Mamo, Y., Crompton, H., Burke, D., & Nickel, C. (2024). Higher education faculty perceptions of chatgpt and the influencing factors: a sentiment analysis of x. *TechTrends*, *68*, 520–534. https://doi.org/10.1007/s11528-024-00954-1

Maral, M. (2024). A bibliometric analysis on academic integrity. *Journal of Academic Ethics*. https://doi.org/10.1007/s10805-024-09519-6

Papamitsiou, Z., Filippakis, M., Poulou, M., Sampson, D. G., Ifenthaler, D., & Giannakos, M. (2021). Towards an educational data literacy framework: enhancing the profiles of instructional designers and e-tutors of online and blended courses with new competences. *Smart Learning Environments*, *8*, 18. https://doi.org/10.1186/s40561-021-00163-w

Pereira, D., Assunção Flores, M., & Barros, A. (2017). Perceptions of Portuguese undergraduate students about assessment: A study in five public universities. *Educational Studies*, *43*(4), 442–463. https://doi.org/10.1080/03055698.2017.1293505

Rodway, P., & Schepman, A. (2023). The impact of adopting AI educational technologies on projected course satisfaction in university students. *Computers and Education: Artificial Intelligence*, *5*, 100150. https://doi.org/10.1016/j.caeai.2023.100150

Rogerson, A. M., & McCarthy, G. (2017). Using internet based paraphrasing tools: Original work, patchwriting or facilitated plagiarism? *International Journal for Educational Integrity*, *13*, 2. https://doi.org/10.1007/s40979-016-0013-y

Romero, M., Reyes, J., & Kostakos, P. (2024). Generative Artificial Intelligence in higher education. In A. Urmeneta & M. Romero (Eds.), *Creative applications of Artificial Intelligence in education* (pp. 129–143). Palgrave Macmillan. https://doi.org/10.1007/978-3-031-55272-4_10

Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning and Teaching*, *6*(1), 342–363. https://doi.org/10.37074/jalt.2023.6.1.9

Sanusi, T. S., Olaleye, S. A., Oyelere, S. O., & Dixon, R. A. (2022). Investigating learners' competencies for artificial intelligence education in an African K-12 setting. *Computer and Open Education*, *3*, 100083. https://doi.org/10.1016/j.caeo.2022.100083

Schumacher, C., & Ifenthaler, D. (2018). Features students really expect from learning analytics. *Computers in Human Behavior*, *78*, 397–407. https://doi.org/10.1016/j.chb.2017.06.030

Spector, J. M., & Ma, S. (2019). Inquiry and critical thinking skills for the next generation: from artificial intelligence back to human intelligence. *Smart Learning Environments*, *6*, 8. https://doi.org/10.1186/s40561-019-0088-z

Stahlberg, F. (2020). Neural machine translation: A review. *Journal of Artificial Intelligence Research*, *69*, 343–418. https://doi.org/10.1016/j.aiopen.2020.11.001

Stein, J. P., Messingschlager, T., Gnambs, T., Hutmacher, F., & Appel, M. (2024). Attitudes towards AI: measurement and associations with personality. *Scientific Reports*, *14*, 2909. https://doi.org/10.1038/s41598-024-53335-2

Stöhr, C., Ou, A. W., & Malmström, H. (2024). Perceptions and usage of AI chatbots among students in higher education across genders, academic levels and fields of study. *Computers and Education: Artificial Intelligence*, *7*, 100259. https://doi.org/10.1016/j.caeai.2024.100259

Walter, Y. (2024). Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*, *21*, 15. https://doi.org/10.1186/s41239-024-00448-3

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(39), 1–27. https://doi.org/10.1186/s41239-019-0171-0

Ifenthaler, D., Cooper, M., Heil, J., & Mascia, M. (2024). Paper Name. In Cochrane, T., Narayan, V., Bone, E., Deneen, C., Saligari, M., Tregloan, K., Vanderburg, R. (Eds.), *Navigating the Terrain: Emerging frontiers in learning spaces, pedagogies, and technologies*. Proceedings ASCILITE 2024. Melbourne (pp. 56-65). https://doi.org/10.14742/apubs.2024.1090

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