Bećirović et al. Smart Learning Environments (2025) 12:67
https://doi.org/10.1186/s40561-025-00422-0

Smart Learning Environments

RESEARCH Open Access

A multidimensional study of AI adoption among University students in teacher education programs

Senad Bećirović[1*], Edda Polz[1] and Isabella Tinkel[2]

*Correspondence:
senad.becirovic@ph-noe.ac.at

[1] University College of Teacher Education Lower Austria, Mühlgasse 67, 2500 Baden, Austria
[2] EPIC Training, 2344 Maria Enzersdorf, Austria

Abstract

The purpose of this study is to determine the factors that affect students' successful and efficient usage of AI in Austrian teacher education programs. To achieve this, a multi-perspective approach was used, combining MAILS, ISS, and TAM3 frameworks. To evaluate the research model, CB-SEM was employed to analyze data collected from 254 students. The results showed that performance outcomes of AI use positively influence perceived ease of AI use, perceived usefulness of AI, and practical application of AI, but not AI attitudes and students' satisfaction with AI. Although AI ethics does not affect perceived ease of AI use and AI usefulness, it positively influences practical application of AI. Technological complexity of AI negatively impacts perceived ease of AI use, but its influence on perceived usefulness of AI, AI attitudes, AI satisfaction, and AI practical application is insignificant. While both perceived usefulness of AI and ease of AI use positively influence AI attitudes and AI satisfaction, perceived ease of AI use does not influence AI satisfaction. Interestingly, AI attitudes and AI perceived usefulness positively influence AI satisfaction, but AI attitudes do not affect AI practical application. Finally, students' satisfaction with AI positively influences AI practical application. The results may help educational policymakers develop and implement necessary policies and guidelines for AI training and use, as well as provide essential resources and technical support. Furthermore, these findings may enhance the design and functionality of AI-powered technologies and support educators and students in improving the quality and effectiveness of AI utilization.

Keywords: Artificial intelligence, Teacher education, AI adoption, AI technological complexity, AI literacy, AI ethics, AI practical application, AI attitudes, AI satisfaction

Introduction

The explosive growth of generative artificial intelligence (GenAI, hereafter referred to as AI) technologies has led to a fundamental shift in society, the economy, and education, transforming learning and teaching practices to an unprecedented extent (Soodan et al., 2024). In a study comparing human- and AI-generated argumentative essays in an English as a second language class, it was discovered that AI-generated output featured more sophisticated and varied vocabulary, while human-generated texts contained more function words and a lower number of advanced vocabulary items (Zindela, 2023). This underlines the potential benefits of AI tools to provide students with useful example output, which can be used to learn and improve their language and various other skills and abilities. As all of these abilities are invaluable in today's rapidly changing (business) world (Bećirović, 2023b), it seems AI technologies only offer boundless opportunities. However, research also underscores the potential danger of the misuse of AI in educational settings when students rely on the "better" AI output and submit it as their own for assessment without any learning effect (Jang et al., 2022). Similarly, aspects such as data privacy and security and the reliability of AI output have been viewed critically (Lepik, 2024; Stracke et al., 2025a, 2025b). Considering this, it is heartening to know that students, while generally enthusiastic about AI tools (Brandhofer & Tengler, 2024; Pinzolits, 2023), are aware of the possible dangers and willing to engage with these ethical issues.

In accordance with the European AI Act, which became effective on August 1, 2024, Austria has been taking steps to face future AI-related challenges and to be compliant with this crucial legislation (Digital Austria, 2024). While AI can contribute significantly to improving the Austrian economy and providing a competitive edge for companies, according to former Secretary of State Florian Tursky (Digital Austria, 2024), its use must be governed and regulated to minimize potential risks. Ethical and data protection issues, as well as the education of users regarding the usage of AI tools, are also among the most important topics (Digital Austria, 2024). In 2024, 63% of people in Austria had at least basic digital knowledge and it is planned to raise this number to 80% by 2030 (Bundeskanzleramt et al., 2024). As part of this, the "Digital Skills for All" program has been launched across Austria (Digital Austria, 2024). Furthermore, all ministries have jointly drawn up a development and implementation plan for AI in which educational measures play a major role (Bundeskanzleramt et al., 2024). Initiatives to improve AI literacy were designed based on data from the Digital Economy and Society Index (DESI) 2024, where Austria ranked above the EU average, as well as a study on AI literacy conducted by the University for Continuing Education in Krems (Bundeskanzleramt et al., 2024). Apart from reducing existing gender biases and encouraging women to engage in AI-related jobs, an evaluation of AI learning software was carried out in 100 pilot schools (Bundeskanzleramt et al., 2024). This goes hand in hand with an initiative to strengthen student competencies regarding AI to prepare them for responsible usage and support teachers with integrating AI-related topics into their teaching (Bundeskanzleramt et al., 2024).

Although AI is a prominent topic in Austria's discourse, as shown by government documents and surveys, there is still a gap in research on students' perspectives regarding AI's role in their educational experiences. However, the PWC Hope & Fears Survey 2024 found that 52% of respondents have used AI at their workplace (it is not specified whether this included educational institutions) in 2024. Especially among GenZ, AI tools are popular, with 67% having used them at work regularly and 6% on a daily basis (PricewaterhouseCoopers, 2024a). In addition, 78% of the Austrian workforce is prepared to adapt to new ways of working with AI, and 65% are convinced that AI tools can help them learn new skills (PricewaterhouseCoopers, 2024a).

Although recent studies have shown that around 50% of student teachers and 75% of teachers in Austria rate the opportunities of AI tools higher than the risks (Brandhofer &

Tengler, 2024), the actual practical application of AI tools depends strongly on their perceived ease of use and usefulness (Kraus et al., 2020; Yildiz Durak, 2023). As students in teacher education programs, who are the focus of this study, form the basis of the future of the educational sector, it is imperative to be aware of their attitudes toward employing AI in their own studies (Ma & Lei, 2024; Zhang et al., 2023). Once they enter their chosen teaching profession, they will assume a pivotal role in shaping how their students interact with AI technologies (Lee, 2024). Hence, it is paramount to consider a wide variety of factors, such as the perceived usefulness and ease of use of AI tools, which may impact students' actual willingness to adopt and apply AI in their own learning. Furthermore, the degree of technological complexity of AI tools, which is closely related to perceived ease of use, may have a significant influence on satisfaction with AI tools. Equally, the degree to which students in teacher education feel they benefit from using AI for their own learning and achieving their learning goals and increasing performance also has an influence on the extent of AI adoption. AI ethics is another crucial aspect that can have a positive or negative impact on students' overall willingness to engage with AI tools (Stracke et al., 2025a, 2025b). However, empirical studies on the relationships among AI performance outcomes, AI learning, AI ethics, AI technology, perceived usefulness of AI, perceived ease of AI use, user satisfaction, attitudes towards using AI, and AI practical application among students in teacher education programs in Austria are scarce. Since the adoption of AI technology among Austrian students has not been thoroughly and systematically studied, this study seeks to fill that gap in the academic literature and offer practical, ethically informed recommendations for meaningfully and effectively using AI technologies in educational processes.

This quantitative, multidimensional study investigates the interrelationship among AI ethics, attitudes toward using AI, AI learning, AI performance outcomes, the complexity of AI technology, perceived usefulness and ease of AI use, user satisfaction with AI, and the practical application of AI. Thus, the study aims to examine the factors that may influence the successful and effective use of AI-powered tools among tertiary-level student teachers. Likewise, this investigation seeks to better understand the understudied variables and their relationships, thereby filling gaps and enriching the existing literature on the adoption of AI technology in education while establishing a robust framework for understanding its application and effectiveness in higher education. The results may assist educators and students in implementing effective teaching and learning strategies to improve the quality and effectiveness of AI usage in higher education. Additionally, the findings may help to improve the functionality and design of AI-driven technologies. Furthermore, they may support educational policymakers in developing and enacting necessary policies and standards for AI usage, as well as for training pre-service and in-service teachers and providing the necessary resources and technical support, all aimed at improving the overall effectiveness of teaching and learning with the aid of AI technology, potentially leading to better educational outcomes.

Literature review

The continued surge in artificial intelligence technologies is significantly changing the face of the educational sector, providing a vast array of new learning opportunities and challenges (Ayanwale & Molefi, 2024). AI tools are now frequently employed by students to obtain required information more efficiently through AI's ability to process vast amounts of data at high speed (Asirit & Hua, 2023; Mohamed et al., 2024; Potter et al., 2024a, 2024b). Such tools can support students in the improvement of their writing skills by providing individual feedback (Brew et al., 2023; Potter et al., 2024b; Pratama & Hastuti, 2024), assisting them in overcoming writer's block, and stimulating creativity (Lepik, 2024; Shanto et al., 2024).

To examine the interrelationships among various factors of AI adoption, the research model of this multidimensional study includes nine variables (Fig. 1) drawn from several established theories of technology acceptance and use. It consists of variables from the Technology Acceptance Model (TAM) (Venkatesh & Bala, 2008), such as perceived usefulness, perceived ease of use, attitudes toward technology use, and technological complexity; user satisfaction derived from the Information Systems Success (ISS) model (DeLone & McLean, 2003); practical applications of AI drawn from Laupichler et al.'s (2023) framework for assessing non-experts' AI literacy; AI ethics and AI learning from MAILS—Meta AI literacy scale (Carolus et al., 2023); and finally, AI performance outcomes as described by Damnjanovic et al. (2013). Such an integrated approach with the models mentioned above enhances explanatory power, enriches predictive capabilities, and provides new insights into students' AI adoption in teacher education programs. Additionally, combining multiple models allows for a more comprehensive analysis of relationships between predictors like the multidimensional AI literacy concept (from MAILS), perceived usefulness and ease of AI use (from TAM), and user satisfaction with AI (from ISS). Therefore, our research model illustrates the hypothesized relationships among factors that may have an influence on the adoption and successful use of AI in tertiary-level educational contexts. This model examines the impact of AI ethics, technological complexity, performance outcomes of AI, and AI learning on the perceived usefulness of AI, the perceived ease of using AI, attitudes toward AI usage, user satisfaction with AI, and practical applications of AI. Additionally, this multidimensional study investigates how AI's perceived usefulness and ease of use affect students' satisfaction with AI and their attitudes toward it, as well as the influence of these two variables on the practical applications of AI. The model suggests a feedback loop, proposing that as students engage successfully with AI-powered tools, complexity is reduced and students' attitudes and perceptions enhanced, leading to more effective and increased adoption of

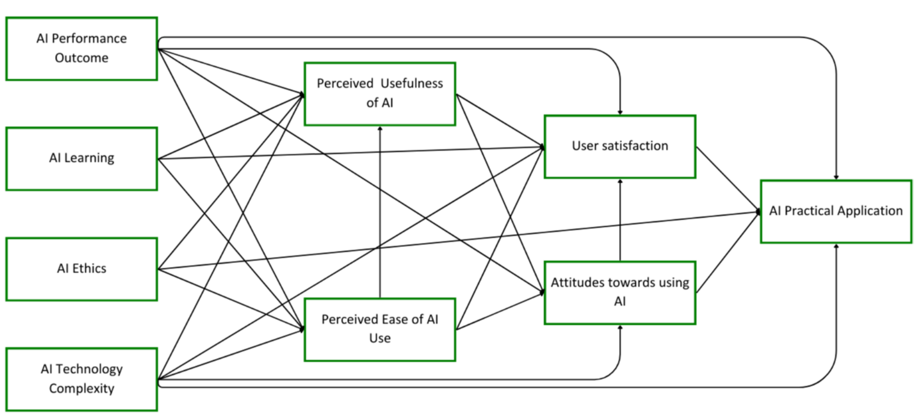

Fig. 1 The research model

AI. Moreover, sustaining positive attitudes requires the ethical application of AI technology to prevent misuse. The following sections clarify and justify the rationale for including each variable in this comprehensive study model and outline their proposed relationships.

AI performance outcomes

One reason to be wary of AI tools, as indicated by the concerns mentioned above, is their impact on students' performance outcomes. However, while an over-reliance on AI tools has been found to negatively impact performance (Khoso et al., 2023), it has been stated that reasonable use of these tools can indeed support students' performance (Montenegro-Rueda et al., 2023), which can further help in reaching the defined learning goals (Brandhofer & Tengler, 2024). When combining AI-generated texts and own input, students were found to improve their performance outcome in terms of content, language and organization (Woo et al., 2024). Students are, however, aware that AI output needs to be viewed critically and its plausibility and applicability to the task at hand need to be verified. While students also regard AI tools as useful support to alleviate stress caused by their studies (Lepik, 2024)—to summarize material, for example—it has been found that AI generated output frequently features rather generic thoughts and repetitive arguments (Asirit & Hua, 2023; Lepik, 2024; PricewaterhouseCoopers, 2023) and has been shown to perpetuate biases that were previously present in the source material (Jang et al., 2022). Clearly, educational systems need to be designed to provide students with the knowledge and skills to use such AI tools ethically as well as effectively (Bećirović & Mattoš, 2024) to be aware of these issues and how to handle them. Therefore, to investigate the influence of students' AI performance outcomes on their AI usage satisfaction, perceived usefulness of AI, and AI practical application, the following hypotheses have been proposed:

AI Performance Outcome significantly predicts AI Practical Application.

AI Performance Outcome significantly predicts User Satisfaction with AI.

AI Performance Outcome significantly predicts Perceived Usefulness of AI.

AI Performance Outcome significantly predicts Attitudes towards using AI.

AI Performance Outcome significantly predicts Perceived Ease of AI Use.

AI learning

Liu and Ma (2024) have found that the actual practical application of AI for learning has been linked to perceived usefulness—the degree to which users believe a technology will support their performance (Venkatesh et al., 2012) —and perceived ease of use—the ability to use a system with minimum effort (Davis, 1989). Furthermore, students are more likely to view AI tools as useful cooperation partners in their learning if they can perceive the benefits of this technology (Delcker et al., 2024). In addition, gender might play a mediating role in the relationship between perceived usefulness and perceived ease of use, thus affecting actual AI usage (Zhang et al., 2023). Male participants scored higher in the area of perceived ease of use and, thus, perceived AI tools as more useful overall and were inclined to use them more willingly (Zhang et al., 2023).

As suggested by TAM, the usefulness of a system will generally be determined by "how well the system performs those tasks" (Venkatesh & Davis, 2000, p. 191) that are relevant for reaching the desired outcome. This is supported by a study on the acceptance of academic advising chatbots, which discovered that perceived ease of use significantly impacted acceptance and usage of these chatbots (Bilquise et al., 2024). However, if users lack the necessary knowledge and skills or the AI application is overly difficult to operate, perceived ease of use as well as perceived usefulness will decline. Yet, as has been stated, ease of use is crucial to the acceptance of and continued work with AI technologies (Al Shamsi et al., 2022; Moriuchi, 2019; Zhang et al., 2023). Thus, in order to explore the significance of students' willingness to employ AI tools in their own learning, the hypotheses below have been drawn up:

AI Learning significantly predicts Perceived Usefulness of AI.

AI Learning significantly predicts User Satisfaction with AI.

AI Learning significantly predicts Perceived Ease of AI Use.

AI technology complexity

It follows that AI tools that are perceived as being easy to use and useful for a particular task will be accepted more readily and employed more enthusiastically, thereby increasing general satisfaction with AI technology (Ma & Lei, 2024). This is also true for a reciprocal relationship between perceived usefulness of AI tools for academic success and user satisfaction (Rokhman et al., 2022). Yet, AI technology can be complex to operate and students who have the skills to employ these AI tools with maximum benefit (Bozkurt, 2023) are at an advantage and likely more enthusiastic about AI technologies. Surprisingly, however, a study among Thai students (Kanont et al., 2024) found that increased ease of use of generative AI tools seemed to make them less attractive for learners rather than increase enthusiasm. This could indicate that a too high degree of intuitive behavior of the AI tool undermines usage motivation. This apparent desire for a certain level of required technical knowledge seems consistent with findings suggesting a positive influence of technical understanding of AI on confidence in using these tools to produce useful outcomes (Bećirović et al., 2025a, 2025b). Further, it would support the finding that students who possess the required technical knowledge are more likely to use AI tools in their own teaching in future (Ma & Lei, 2024).

Yet, overly complex AI technology naturally triggers a decrease in perceived ease of use, diminishing students' enjoyment (Li et al., 2021) and their positive attitude towards AI tools (Al Shamsi et al., 2022), thereby reducing general satisfaction. In more extreme cases, AI can even trigger stress and anxiety in users, making them less likely to use these tools (Bandura et al., 1999; Wang et al., 2023). Considering the previous studies and aiming to investigate the influence of AI technology complexity further, the following hypotheses have been proposed:

AI Technology Complexity significantly predicts AI Practical Application.

AI Technology Complexity significantly predicts Attitudes towards using AI.

AI Technology Complexity significantly predicts Perceived Ease of AI Use.

AI Technology Complexity significantly predicts User Satisfaction with AI.

AI Technology Complexity significantly predicts Perceived Usefulness of AI.

AI ethics

Provided that AI tools have an appropriate level of complexity, perceived ease of use and usefulness are high, and their use is generally supported, students' attitude towards AI ethics can still pose a significant challenge. A variety of guidelines, which mainly focus on data and algorithms, have been established by international organizations such as the United Nations as well as by local governments and institutions (Bećirović & Mattoš, 2024). While issues such as data privacy, consent and ownership, along with topics such as biases of algorithms and transparency are crucial, the use of AI technology in the educational sector requires a wider range of ethical considerations. Among those are the definition of what constitutes useful knowledge, student agency and the validity and fairness of assessments (Holmes et al., 2023). Similarly, proven biases in certain AI systems used by Northpoint and Amazon (Jang et al., 2022) must be considered when working with AI technology in education to ensure such biases can be detected and viewed critically. Likewise, the issue of plagiarism and its facilitation by AI's ability to create new text compositions based on existing information without citations needs to be given attention (McCoy et al., 2023). Before the introduction of AI, the concept of plagiarism and the rules for avoiding it were clearly defined, rule-breaking could be identified quite easily, and the consequences of breaking these rules were straightforward (Dautbašić & Bećirović, 2022). Since the advance of AI, plagiarism has been facilitated through the automatic generation of text which usually paraphrases other authors but does not provide citations (Hutson, 2024). A study by AI-detection tool provider Turnitin found that 3.5% of texts analyzed contained 80–100% AI-generated text, while 9.6% contained 20% AI-generated text (Chechitelli, 2023). Such irresponsible usage of AI for text creation might also lead to a decline in critical thinking ability in students (PricewaterhouseCoopers, 2023).

It is promising, therefore, that despite an overall positive attitude, students are wary of using AI with respect to the processing of (personal) data, preferring to ensure that their data is only used with their explicit consent (Al Shamsi et al., 2022). Thus, trust in AI technologies is a crucial topic. However, the learning processes of these technologies are a kind of "black box". It is hardly possible for users to determine where an AI sources its information and how it arrives at the output it provides (Jang et al., 2022) which, in turn, can influence students' trust in the security of their data when using AI tools (Gross et al., 2020).

This weariness indicates that students are aware of the possible ethical limitations of AI technology and are endeavoring to genuinely apply these tools in their learning process in a safe and responsible way and after critical reflection (Bećirović et al., 2025a, 2025b). This illustrates students' ability to employ critical thinking when using AI tools, which is a key aspect of shaping their attitudes towards using AI. Austria has seen a certain amount of skepticism among its population regarding the use of AI tools in business and educational settings, with many actually fearing a decline in critical thinking and, especially in education, a decrease in the quality of written work and a rise in cheating and plagiarism (PricewaterhouseCoopers, 2023, 2024b). Even a lowering of the educational standards and the dehumanization of the learning experience by overvaluing human–machine-interaction has been suggested by students (Holmes et al., 2023).

However, an overly critical view of AI can hinder the effective and efficient use of such technologies as students are then not willing to provide enough data for meaningful AI functionality (Al Shamsi et al., 2022), rely on AI output at all or spend an extended period of time verifying output so that any advantages gained through AI tools are once again lost. This implies that a certain level of trust in AI technologies is required for students to actually apply these tools and perceive them as useful for their learning (Shahzad et al., 2024), making the issue of transparency even more important. Likewise, to delve deeper into the significance of the influence of students' AI ethics towards AI adoption, the following hypotheses have been formulated:

AI Ethics significantly predicts Perceived Usefulness of AI.

AI Ethics significantly predicts AI Practical Application.

AI Ethics significantly predicts Perceived Ease of AI Use.

Methods

Participants

This study involved 254 students from four distinct teacher education institutions in Austria. Convenience sampling, the most common nonprobability sampling technique (Edgar & Manz, 2017), was used to select participants. The research sample included 212 females (83.5%), 39 males (15.4%), and 3 participants (1.2%) who chose not to disclose their gender. This data indicates a gender imbalance; however, the gender imbalance in our research sample reflects broader trends in Austrian higher education, where most students enrolled in multiple higher education programs are female. Recent data indicate that women make up about 56% of university students in Austria, with even higher percentages seen in university colleges of teacher education, where 77% of the student body is female (More Women Than Men Study at Austrian Universities, 2023). Therefore, overrepresentation of female students in our study aligns with national enrollment patterns and adequately reflects the population studied. Regarding the participants' fields of study, this research sample comprises 104 students pursuing primary school teaching (40.9%), 26 students specializing in elementary pedagogy (10.2%), 30 students pursuing secondary school teaching (11.8%), 32 students specializing in digital education, media, and information technology (12.6%), and 62 students pursuing other pedagogical disciplines (24.4%). Participants ranged in age from 18 to 60 years (mean $=$ 35.3, $SD = 11.5$). The total number of variables observed can be used to calculate the sample size (Rokhman et al., 2022). The minimum number of participants should be at least five times the number of variables (Memon et al., 2020). Furthermore, according to Yew et al. (2022), the minimum number of participants the study should include is ten times the number of variables. Hair et al. (2014), however, recommend that there should be at least 15–20 times as many participants as there are variables. With 254 participants, our study includes 28.2 times the number of variables, which is nine, as presented in Fig. 1. Consequently, the sample of 254 participants in the study comprises more participants than suggested by the aforementioned academics.

Instruments and procedures

An online questionnaire was administered to gather data. The beginning of the questionnaire included questions related to students' demographic characteristics, such as field of study, gender, and age. The rest of the questionnaire featured statements concerning the following variables: AI ethics (e.g., "I can incorporate ethical considerations when deciding whether to use data provided by an AI"), attitudes towards using AI (e.g., "I have positive feelings towards the use of AI in learning"), AI learning (e.g., "I can keep up with the latest innovations in AI applications"), AI performance outcomes (e.g., "Use of the AI tools has improved my overall learning performance"), the technological complexity of AI (e.g., "Using AI in learning is a complex activity"), perceived usefulness of AI (e.g., "Using AI enhances my effectiveness in learning"), perceived ease of AI use (e.g., "I find AI easy to use in learning"), user satisfaction with AI (e.g., "Overall, I am satisfied with the AI"), and the practical application of AI (e.g., "I can critically evaluate the implications of artificial intelligence applications in at least one subject area"). The survey instrument was adopted from previous studies, piloted with Austrian participants, and reliability (Table 1) as well as convergent and discriminant validity (Table 4) were ensured.

Students' responses were evaluated using a 7-point Likert scale, where 1 represented strongly disagree and 7 indicated strongly agree. Cronbach's alpha was utilized to assess the reliability of the data. The results of the reliability test revealed that all Cronbach's alpha coefficients were acceptable, ranging from .76 to .95. Table 1 displays all variables, including the reliability coefficients and their respective sources.

Google Survey was used to collect the data. Before data collection, university administration and students provided informed consent. The objectives of the questionnaire, as well as the instructions for filling it out, were provided at the beginning of the questionnaire. Students spent about 20 min filling out the questionnaire.

Data analysis

SPSS (Statistical Package for the Social Sciences) and AMOS, version 29.0, were utilized to analyze the data. The Cronbach's alpha reliability test was used to assess data reliability, while the distribution's normality was tested using skewness and kurtosis. Additionally, prior to testing the hypothesized model, means, standard deviations, frequencies, and correlations were calculated. To examine the hypothesized model, Confirmatory Factor Analyses (CFA) were performed (Anderson & Gerbing, 1988). After confirming acceptable model fit and discriminant and convergent validity, the structural model was tested using covariance-based structural equation modeling (CB-SEM). CB-SEM

Table 1 Instruments for data collection

Variables	α	Sources
AI Ethics (ETH)	.76	Carolus et al. (2023)
Attitudes towards using AI (ATU)	.86	Adapted from Teo (2009)
AI Learning (LRN)	.91	Carolus et al. (2023)
Performance outcome of AI (PO)	.87	Adapted from Damnjanovic et al. (2013)
Technology complexity of AI (TC)	.80	Adapted from Teo (2009)
Perceived usefulness of AI (PU)	.95	Adapted from Teo (2009)
Perceived ease of AI use (PEOU)	.95	Adapted from Teo (2009)
User satisfaction with AI (US)	.77	Adapted from Freeze et al. (2010)
Practical application of AI (PA)	.95	Laupichler et al. (2023)

is chosen because it evaluates prediction and estimation (Al-Adwan et al., 2022), accurately predicts sophisticated models (Hair et al., 2017), and can assess conceptualized models derived from prior theoretical inferences (Barrett et al., 2021). Moreover, CB-SEM is a robust statistical technique capable of identifying relationships in social science research that other methods might overlook (Hair et al., 2017). It is particularly effective with models that incorporate second-level constructs or model development (Kosiba et al., 2022), which aligns with the conceptual model of this study.

Results

Initial analysis

The participants achieved the highest scores in user satisfaction with AI ($M = 4.67$; $SD = 1.45$) and ethical use of AI ($M = 4.50$; $SD = 1.33$), indicating that they are quite satisfied with the AI outputs and seriously consider ethical issues when applying AI for educational purposes. However, the application of AI for learning ($M = 2.80$; $SD = 1.50$) and its performance outcomes ($M = 2.70$; $SD = 1.68$) fall below average, highlighting the significant need for training to use AI tools effectively and productively in educational contexts. Detailed scores for all variables' means and standard deviations are presented in Table 2.

Analysis of skewness and kurtosis revealed scores ranging from −1.18 to .85, signifying that all values conform to the criteria for normally distributed data (Hair et al., 2014). The correlation analysis between the constructs ranged from $r = -.40$ to $r = .80$. The strongest correlation was found between attitudes towards the use of AI and perceived usefulness of AI ($r = .80$; $p < .001$), as well as perceived ease of AI use ($r = .79$; $p < .001$). In contrast, the most considerable negative correlation was observed between the technological complexity of AI and user satisfaction with AI ($r = -.40$; $p < .001$) and perceived ease of AI use ($r = -.39$; $p < .001$), indicating a significant need for training students on how to use AI tools, as well as making them more user-friendly and suitable for students' expectations and needs.

The results of the measurement model

A confirmatory factor analysis (CFA) utilizing maximum likelihood estimation has been performed to assess the measurement model. The multivariate normality of the collected data was evaluated using Mardia's (1970) normalized multivariate kurtosis

Table 2 Descriptive analysis, normality, and reliability

Variables	M	SD	Skew	Kurt	ETH	ATU	LRN	PO	TC	PU	PEOU	US	PA
ETH	4.5	1.33	−.37	−.42	1	.18**	.52**	.23**	−.10	.20**	.23**	.20**	.47**
ATU	3.20	1.61	.37	−.72		1	.37**	.72**	−.28**	.80**	.79**	.65**	.54**
LRN	2.80	1.50	.62	−.39			1	.44**	−.22**	.41**	.52**	.35**	.55**
PO	2.70	1.68	.85	−.18				1	−.26**	.84**	.71**	.51**	.53**
TC	2.88	1.41	.69	.05					1	−.32**	−.39**	−.40**	−.30**
PU	3.09	1.81	.55	−.86						1	.82**	.64**	.52**
PEOU	3.50	1.91	.19	−1.18							1	.64**	.66**
US	4.67	1.45	−.43	−.14								1	.56**
PA	4.24	1.81	−.27	−.99									1

** Correlation is significant at the 0.01 level (2-tailed) score. The multivariate kurtosis metric, known as Mardia's coefficient, was calculated to be 213.9. This outcome is below the threshold value of 1244, derived from the equation p (p + 2), where p denotes the total number of observed variables (34 [36] = 1244). Consequently, it is presumed that the data in this investigation follows a multivariate normal distribution (Raykov & Marcoulides, 2008).

The standardized estimates (SE) for each item in Table 3 demonstrate that the findings of the CFA reveal all items exhibited acceptable loadings and significantly contributed to the explanation of their respective constructs (Hair et al., 2014; Hara et al., 2010). Hair et al. (2014) stated that when evaluating a model, the χ2 value, degrees of freedom, RMSEA (root mean square error of approximation), and CFI (comparative

Table 3 Results of the measurement model

		USE	SE	*t*-Value	*P*	CR	AVE
	PO1	1.000	.730				
AI Performance outcome (PO)	PO2	1.254	.884	18.114	***	.850	.656
	PO3	1.264	.808	12.812	***		
	LRN1	1.000	.947				
AI Learning (LRN)	LRN2	.836	.783	14.527	***	.881	.713
	LRN3	.820	.793	14.813	***		
	ETH1	1.000	.578				
AI Ethics (ETH)	ETH2	1.187	.740	8.551	***	.782	.551
	ETH3	1.511	.879	8.970	***		
	TC1	1.000	.846				
AI Technology complexity (TC)	TC2	.950	.809	11.410	***	.803	.580
	TC3	.702	.609	9.250	***		
	PU1	1.000	.912				
	PU2	.929	.902	23.600	***		
Perceived usefulness of AI (PU)	PU3	1.036	.905	23.726	***	.956	.812
	PU4	1.049	.922	25.313	***		
	PU5	.946	.864	20.988	***		
User satisfaction (US)	US1	1.000	.858			.888	.800
	US2	1.127	.929	17.874	***		
	PA1	1.000	.731				
	PA2	1.130	.731	14.448	***		
	PA3	1.056	.738	11.265	***		
Practical application of AI (PA)	PA4	1.205	.806	12.606	***	.913	.600
	PA5	1.211	.750	11.761	***		
	PA6	1.214	.854	13.370	***		
	PA7	1.298	.803	12.633	***		
	PEOU1	1.000	.863				
	PEOU2	1.105	.908	20.797	***		
Perceived ease of AI use (PEOU)	PEOU3	1.092	.951	23.092	***	.952	.833
	PEOU4	1.065	.926	21.714	***		
	ATU1	1.000	.592				
Attitudes towards using AI (ATU)	ATU2	1.500	.837	10.917	***	.869	.630
	ATU3	1.729	.946	10.830	***		
	ATU4	1.349	.758	8.740	***		

USE = unstandardized estimates; SE = standardized estimates; CR = composite reliability; AVE = average variance extracted; * * * = < 0.01

fit index) or TLI (Tucker-Lewis index) are sufficient indicators for consideration. According to Carmines and McIver (1981), a good fit is characterized by a minimum fit function (χ2) and a ratio of χ2 to its degree of freedom (χ2/df) whose value is below 3.0. This research's measurement model, with a score of $\chi 2 = 857.513$ and $\chi 2/df = 1.790$, demonstrated a good fit. Hair et al. (2014) regard an RMSEA of 0.03 to 0.08 with 95% confidence as adequate. Likewise, this measurement model's output with $RMSEA = .056$ and $PCLOSE = .055$ revealed acceptable scores. The $TLI = .943$ and $CFI = .951$ of the measurement model of this study were greater than 0.90, indicating a good fit (Hair et al., 2014). An *SRMR* (standardized root mean residual) value of less than 0.09 (Hair et al., 2014) is a good indicator of a well-fitting model, and the results of testing this model, which came in at .054, meet this requirement. The indications, as mentioned above, confirmed that the measurement model for the present study fits the data well.

Average variance extraction (AVE) and composite reliability (CR) were used to assess each construct's convergent validity. Since the AVE and CR values in this study fall above the threshold values of .50 and .70 (Fornell & Larcker, 1981) (Table 4), all of the AVE (.551 to .833) and CR values (.782 to .956) were considered acceptable. To evaluate discriminant validity, the square of the correlation between the constructs and the AVE scores was employed. The AVE scores are expected to be higher than the square of the correlation value (Eraslan Yalcin & Kutlu, 2019; Escobar-Rodriguez & Monge-Lozano, 2012). The convergent and discriminant validity scores are shown in Table 4.

The results of the hypothesized relationships

The results indicated that the structural model ($\chi 2 = 876.798$, $\chi 2/df = 1.808$, $TLI = .942$, $CFI = .949$, $SRMR = .0537$, $RMSEA = .057$, $PCLOSE = .038$) demonstrated a good model fit. Considering $p < .05$ as a threshold for significance, fourteen of the twenty-four hypotheses (Table 5) were supported (H1, H2, H4, H5, H6, H9, H12, H13, H15, H18, H19, H20, H21, and H24), while ten were refuted (H3, H7, H8, H10, H11, H14, H16, H17, H22, and H23).

The results of the structural model indicated that the performance outcome of AI usage significantly predicted perceived ease of AI use (H 1) ($\beta = .59$, $p < .001$), perceived usefulness of AI (H 5) ($\beta = .78$, $p < .001$), and practical application of AI (H 20) ($\beta = .22$, $p = .049$). However, it did not have a significant impact on attitudes toward

Table 4 Validity analysis (Convergent and discriminant)

	AVE	CR	MSV	MaxR(H)	PA	PO	LRN	ETH	TC	PU	PEOU	US	ATU
PA	.600	.913	0.438	.918	**.775**								
PO	.656	.850	0.903	.868	.452	**.810**							
LRN	.713	.881	0.425	.923	.652	.523	**.844**						
ETH	.551	.782	0.438	.836	.662	.264	.576	**.743**					
TC	.580	.803	0.209	.833	−.297	−.339	−.307	−.136	**.762**				
PU	.812	.956	0.903	.957	.399	.950	.441	.205	−.397	**.901**			
PEOU	.833	.952	0.745	.958	.487	.777	.604	.288	−.457	.840	**.913**		
US	.800	.888	0.573	.901	.493	.636	.478	.289	−.456	.727	.755	**.894**	
ATU	.630	.869	0.773	.927	.393	.859	.450	.226	−.361	.879	.863	.757	**.794**

Table 5 The results of testing hypothesized relationships

Hypotheses	Predictor variables	Relati-onships	Criterion variables	USE	SE	T value	*P*	Label
H1	PO	→	PEOU	.80	.59	8.26	***	Supported
H2	LRN	→	PEOU	.29	.25	3.36	***	Supported
H3	ETH	→	PEOU	− .06	− .03	− .52	.606	Not Supported
H4	TC	→	PEOU	− .23	− .19	− 3.62	***	Supported
H5	PO	→	PU	1.07	.78	9.13	***	Supported
H6	LRN	→	PU	− .23	− .19	− 3.77	***	Supported
H7	ETH	→	PU	.034	.02	.48	.634	Not Supported
H8	TC	→	PU	− .05	− .04	− 1.19	.236	Not Supported
H9	PEOU	→	PU	.34	.33	4.81	***	Supported
H10	PO	→	ATU	.06	.07	.42	.674	Not Supported
H11	TC	→	ATU	.04	.09	1.16	.246	Not Supported
H12	PEOU	→	ATU	.26	.42	5.24	***	Supported
H13	PU	→	ATU	.30	.49	2.74	.006	Supported
H14	PO	→	US	− .96	− .87	− 1.91	.057	Not Supported
H15	LRN	→	US	.26	.27	2.25	.024	Supported
H16	TC	→	US	− .11	− .11	− 1.58	.115	Not Supported
H17	PEOU	→	US	− .001	− .001	− .07	.995	Not Supported
H18	PU	→	US	.79	.99	1.96	.050	Supported
H19	ATU	→	US	.59	.45	3.01	.003	Supported
H20	PO	→	PA	.20	.22	1.97	.049	Supported
H21	ETH	→	PA	.71	.59	6.99	***	Supported
H22	TC	→	PA	− .07	− .08	− 1.34	.181	Not Supported
H23	ATU	→	PA	− .18	− .16	− 1.16	.244	Not Supported
H24	US	→	PA	.23	.28	2.85	.004	Supported

*SE = standardized estimates; * * * p < 0.001; ETH = AI Ethics; ATU = Attitudes towards using AI; LRN = AI Learning; PO = Performance outcome of AI;

TC = Technology complexity of AI; PU = Perceived usefulness of AI; PEOU = Perceived ease of AI use; US = User satisfaction with AI; PA = Practical application of AI

AI use (H 10) ($\beta = .07$, $p = .674$) and students' satisfaction with AI (H 14) ($\beta = -.87$, $p = .057$). Additionally, AI learning significantly influenced perceived ease of AI use (H 2) (β = .25, $p < .001$), perceived usefulness of AI (H 6) ($\beta = -.19$, $p < .001$), and students' satisfaction with AI (H 15) ($\beta = .27$, $p = .024$). While there was an insignificant relationship between AI ethics and perceived ease of AI use (H 3) ($\beta = -.03$, $p = .606$) and perceived usefulness of AI (H 7) ($\beta = .02$, $p = .634$), the relationship between AI ethics and practical application of AI (H 21) was significant ($\beta = .59$, $p < .001$). Furthermore, the technological complexity of AI significantly impacted perceived ease of AI use (H 4) (β = − .19, $p < .001$) but did not have a significant effect on perceived usefulness of AI (H 8) ($\beta = -.04$, $p = .236$), attitudes toward AI use (H 11) ($\beta = .09$, $p = .246$), user satisfaction with AI (H 16) (β = -11, $p = .115$), and practical application of AI tools (H 22) ($\beta = -.08$, $p = .181$). Moreover, perceived ease of AI use significantly affected the perceived usefulness of AI (H 9) ($\beta = .33$, $p < .001$) and attitudes toward AI use (H 12) ($\beta = .42$, $p < .001$) but had an insignificant effect on user satisfaction with AI (H 17) ($\beta = -.001$, $p = .995$). Further, the perceived usefulness of AI significantly influenced attitudes toward AI use (H 13) ($\beta = .49$, $p < .006$) and user satisfaction with AI (H 18) ($\beta = .99$, $p = .050$). Similarly, attitudes toward AI use significantly predicted user satisfaction with AI (H 19) ($\beta = .45$, $p = .003$) and insignificantly predicted the practical application of AI (H 23) ($\beta = -.16$, $p = .244$). Finally, user satisfaction with AI significantly influenced the practical application of AI (H 24) ($\beta = .28$, $p = .004$). All relationships between the measured constructs are presented in Table 5.

In the research model, five endogenous variables were specified: perceived ease of AI use, perceived usefulness of AI, attitudes towards AI use, user satisfaction with AI, and practical application of AI. The first variable, perceived ease of AI use, which accounted for 69% of the variance, was strongly explained by the predictors ($R^2 = 0.69$). AI performance outcome was the primary explanatory factor ($\beta = 0.59$, $p < 0.001$), with AI learning ($\beta = 0.25$, $p < 0.001$) and technology complexity ($\beta = -0.19$, $p < 0.001$) also significantly explaining perceived ease of AI use. AI ethics had insignificant explanatory power.

Perceived usefulness of AI was the most strongly explained, with 95% of its variance accounted for by predictors ($R^2 = 0.95$). This variable was primarily influenced by AI performance outcome ($\beta = 0.78$, $p < 0.001$) and perceived ease of AI use ($\beta = 0.33$, $p < 0.001$), indicating these are the most critical drivers of perceived usefulness of AI. In comparison, AI learning had a smaller yet significant effect ($\beta = -0.19$, $p < 0.001$), while AI ethics and technology complexity were non-significant predictors.

Furthermore, attitudes towards AI use had a high explained variance as well ($R^2 = 0.83$), with perceived usefulness ($\beta = 0.49$, $p = 0.006$) and perceived ease of use ($\beta = 0.42$, $p < 0.001$) as significant predictors, followed by performance outcome ($\beta = 0.07$) and technology complexity ($\beta = 0.09$), which were non-significant predictors.

Similarly, user satisfaction with AI was explained at a moderate-to-high level ($R^2 = 0.70$). The impact of perceived usefulness ($\beta = 0.99$, $p = 0.050$), attitudes towards using AI ($\beta = 0.45$, $p = 0.003$), and AI learning ($\beta = 0.27$, $p = 0.024$) contributed significantly, while AI performance outcome, AI technology complexity, and perceived ease of AI use did not.

Finally, the practical application of AI accounted for 60% of the variance ($R^2 = 0.60$). The significant contributors were user satisfaction ($\beta = 0.28$, $p = 0.004$), AI ethics ($\beta = 0.59$, $p < 0.001$), and AI performance outcome ($\beta = 0.22$, $p = 0.049$), with non-significant effects from AI technology complexity and attitudes toward AI (Fig. 2).

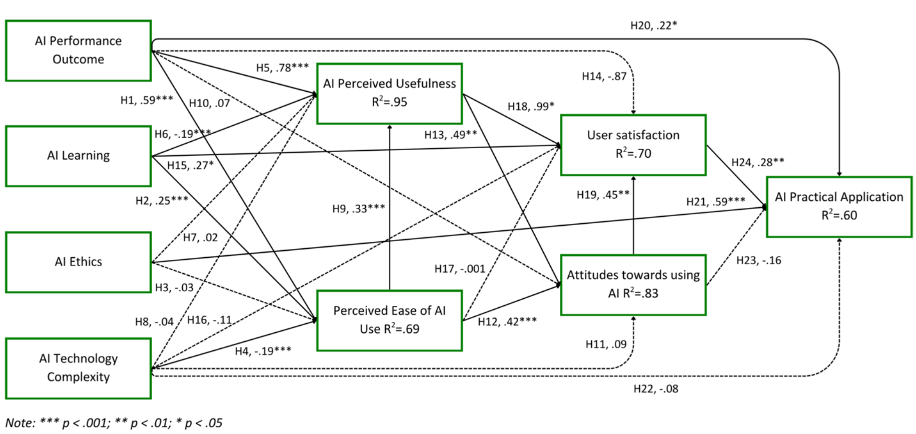

Fig. 2 The results of the hypothesized relationships

Discussion

This study investigates the interrelationship between AI ethics, attitudes toward using AI, AI learning, AI performance outcomes, AI technology complexity, and the perceived usefulness and ease of use of AI, along with user satisfaction and the practical application of AI. Its aim is to examine the variables that may influence the success and effectiveness of AI utilization among tertiary-level students. By exploring these understudied variables and their interactions, this study seeks to enhance understanding of the current literature, fill existing gaps, and contribute to the theory of adopting AI technology in education while also providing a solid foundation for improving the application and effectiveness of AI technology use in higher education. Therefore, this study may contribute to the field by providing valuable insights into learner behavior and preferences regarding AI adoption, usage, and satisfaction, which can support educators and educational institutions in making decisions about the increasing implementation of AI in the pedagogical context (Ma & Lei, 2024; O'Dea & O'Dea, 2023). The next sections discuss the statistically significant relationships as well as those that did not show any significant relationships.

Significant relationships

In line with Kashive et al. (2020), our results indicated that the perceived ease of using AI was positively and significantly influenced by the performance outcome of AI (H1), suggesting that the accuracy, speed, and engagement associated with using AI tools may help students achieve their goals and that they find employing AI tools convenient. Similarly, in alignment with Ahn (2024), who discovered that AI usage is significantly affected by self-efficacy in AI learning, our findings demonstrated that AI learning, which, along with AI problem-solving, is a subdimension of AI self-efficacy (Carolus et al., 2023), is also a significant and positive predictor of the perceived ease of AI use (H2), confirming that AI tools are user-friendly and easy for students to adopt in their learning processes. However, AI learning was identified as a negative predictor of perceived usefulness of AI (H6), suggesting that students have certain reservations regarding AI outputs, including concerns about transparency, privacy and data protection, trust, expectation mismatch, and loss of control. Nonetheless, the results indicated that AI learning is a significant and positive predictor of students' satisfaction with AI (H15) in general, signifying that when students use AI-powered tools, they appreciate the personalized feedback, flexibility, and engagement provided by AI-powered solutions. Nevertheless, students require training on how to use AI tools effectively, meaningfully, and ethically for academic purposes (Grájeda et al., 2024).

Similar to the findings of Falebita and Kok (2024), who identified a positive relationship between technological readiness and perceived ease of AI use, and Ahn (2024), who noted a connection between AI technicality and AI use, our study discovered that perceived ease of AI use was negatively affected by AI technological complexity (H4). This indicates that our students are not yet fully prepared for the effective employment of AI in academic processes. Furthermore, Venkatesh and Bala (2008) suggested that adequate training and instruction, along with user-friendly design, can mitigate the adverse effects of technological complexity on user perception. Therefore, the results of this study show that students' technical proficiency and mental effort in using AI do not result in positive opinions regarding the usability of AI. This implies that students in pedagogical (non-technical) programs require training in AI technologies, which would likely improve and reduce the technological complexity of AI and enhance its efficient use.

AI performance results are essential for people to embrace and utilize AI products. Our findings showed that AI performance outcomes positively and significantly impacted the perceived usefulness of AI (H5), which is consistent with Saavedra et al. (2023), who discovered that perceived usefulness is influenced by process and output quality. Therefore, students are more likely to view technology as useful when they receive outcomes and tailored feedback, provided that AI technology meets their needs and assists them in completing their assignments (Ji et al., 2024). Our results indicate that participants are willing to successfully integrate AI tools into their school activities and potentially enhance their academic performance.

Consistent with earlier investigations (Albayati, 2024; Alejandro et al., 2024; Almogren et al., 2024), our results demonstrated that the perceived ease of AI use positively predicted the perceived AI usefulness (H9), suggesting that students who perceive the ease of use of AI tools are likely to find them convenient and employ them regularly in their academic tasks. Furthermore, our results corroborate the previous findings (Albayati, 2024; Alejandro et al., 2024) by showing that perceived ease of AI use significantly and positively predicted attitudes toward AI engagement (H12). This implies that the user-friendliness of AI tools enhances students' attitudes and their actual usage, as the ease of employing technology directly influences its adoption. Nja et al. (2023) also found that university professors' perceptions of AI-powered technologies were significantly impacted by their perceived ease of use.

In accordance with the prior examination of university students (Almogren et al., 2024; Falebita & Kok, 2024) and instructors (Nja et al., 2023), the perceived usefulness of AI-powered tools significantly impacted students' attitudes toward AI use (H13). The results advocate that students believe that AI-powered tools may significantly help them with their school assignments and improve their efficiency and performance in academic tasks. Similarly, students' (Falebita & Kok, 2024) and teachers' (Nja et al., 2023) attitudes towards AI benefits significantly impact AI adoption (Chibisa et al., 2022; Toros et al., 2024), as the perception of AI usefulness and benefits influences efforts and investment (Condie & Livingston, 2007).

Furthermore, our study found a significant and positive influence of the perceived usefulness of using AI-powered tools on students' satisfaction with them (H18), which is consistent with earlier research (Xing & Jiang, 2024; Yu et al., 2024) demonstrating that the perceived usefulness of using ChatGPT is a significant predictor of user satisfaction with ChatGPT. The results indicate that AI tools live up to the students' expectations, that they benefit from them in terms of time saving, efficiency, problem-solving, and solution finding, and that they are ultimately willing to continue using them. Similar to Sargin's (2024) findings, our results also revealed a significant positive relationship between attitudes toward AI and satisfaction with AI use (H19), implying that students perceive AI technologies as useful, relevant, and practical, which may increase AI adoption and ultimately improve their AI literacy, learning and performance on school assignments.

Our results demonstrated a significant positive relationship between AI performance outcomes and AI practical application (H20), maintaining that students are satisfied with AI's output, including the personalized feedback they receive, adaptive learning and mentoring paths, speed of access to information and its sources, and problem-solving. As a result, the performance of AI tools motivates and engages participants, which may drive them to increase their AI literacy and abilities, as well as apply AI in more systematic, meaningful, and ethical ways in their everyday tasks. Similarly, our results showed a significant positive relationship between AI ethics and AI practical application (H21). Holmes et al. (2019) pointed out that AI literacy, which includes AI ethics, is critical for responsible and meaningful AI usage. Therefore, our results suggest that students in Austrian educational programs seriously consider ethics when using AI tools. This approach could be further enhanced by systematic strategies for teaching AI literacy and ethics. When students are taught how to use AI ethically, they are more likely to employ AI tools effectively, responsibly, and meaningfully, which leads to systematic and structured approaches to AI integration into daily activities. Finally, in line with previous studies (Cai et al., 2023; Kashive et al., 2020; Yu et al., 2024), which demonstrated that user satisfaction with AI positively influenced AI behavioral intention, our study demonstrated that students' satisfaction with AI significantly impacted their AI practical applications (H24). This implies that AI outputs such as real-time communication, source provision (Piotrkowicz et al., 2021), problem-solving, translation tools, and hands-on and interactive experiences ensure student satisfaction, which is the driving force for the practical application of AI technologies.

Insignificant relationships

In agreement with Ko and Leem (2021), the findings of our study showed that AI ethics had no significant impact on the perceived ease of use (H3) and usefulness of AI (H17). This suggests that students may have prioritized AI functionality, efficiency, usability, and outputs over ethical considerations when using AI. The reason for such association may also be attributed to students' low level of awareness and knowledge regarding the ethical application of AI (Jobin et al., 2019). Therefore, modern educational systems ought to prioritize the teaching of AI literacy, including the aspect of AI ethics. Likewise, educators should take a balanced approach to teaching, giving careful consideration to both the practical and ethical aspects of AI.

As posited by Falebita and Kok (2024), the perceived usefulness of AI was found to be positively impacted by technological readiness. However, our results indicated that the technological complexity of AI did not significantly predict the perceived usefulness of AI (H8), indicating that AI complexity does not impede AI usefulness because AI benefits in terms of achieving study objectives outweigh AI complexity (Holmes et al., 2019). Similarly, whereas Ahn (2024) discovered a significant relationship between AI technicality and AI usage, our findings corroborate Falebita and Kok's (2024) findings, showing the insignificant relationship between AI technological complexity and attitudes toward AI use (H11) and AI user satisfaction (H16). These findings strengthen earlier assertions that students may prioritize the advantages of AI in terms of academic support, problem-solving, efficiency, speed, and the quality of information and resources they offer and that the technological complexity of AI does not hinder usage nor adversely affect attitudes and perceived usefulness of AI tools. Furthermore, students are often digital natives (Prensky, 2001), and their adaptability to new technologies, such as AI, may mitigate its complexity (Bećirović, 2023a). Finally, instructor guidance, peer assistance, and tutorials may reduce the negative impact of AI complexity on students' attitudes toward them and lead to their productive and effective application in learning processes.

Students' opinions on AI tools can be influenced by a wide range of factors, including expectations, biases, peer and instructor recommendations, AI design, use experience, performance outcomes, and user-friendliness. While Bation and Pudan (2024) found a significant relationship between AI attitudes and learning outcomes, our results indicated an insignificant relationship between AI performance outcomes and students' attitudes toward AI-powered tools (H10), suggesting that students' expectations might have a bigger impact on how they feel about AI; if these expectations are not entirely met, they might feel neutral or even negative toward it. Similarly, the results indicated an insignificant relationship between AI performance outcomes and user satisfaction with AI (H14), proposing that students' goals and expectations from AI tools are not fully met. However, it should be noted that, whilst performance outcomes are objective, satisfaction is subjective (Venkatesh et al., 2003). Students may place a higher value on learning than on AI technical performance. Therefore, if AI tools do not sufficiently engage students and do not align with their learning styles and preferences (Kulik & Fletcher, 2016), they will not be fully satisfied. In addition, students' experience or familiarity with specific AI tools may influence their satisfaction, requiring more student-centred AI tool design as well as training and improvements in students' AI literacy for effective AI employment.

In contrast with the previous studies (Xing & Jiang, 2024; Yu et al., 2024), which found that the perceived ease of ChatGPT use is a significant predictor of AI user satisfaction, our study showed an insignificant association between perceived ease of AI use and AI user satisfaction (H17), suggesting that students, as digital natives, more adaptable to new technologies, do not consider ease of AI use as a critical factor for AI satisfaction. Furthermore, factors such as students' technological proficiency, type of technological tools (Venkatesh & Bala, 2008), and focus on learning outcomes may outweigh the ease of AI use. To overcome obstacles and successfully use AI technologies, students require assistance in the form of training and resources. This can improve both the tools' usability and students' satisfaction with their use.

While Ahn (2024) discovered a significant relationship between AI technicality and AI use, our findings support Falebita and Kok's (2024) findings, indicating that AI technological complexity had an insignificant impact on the practical application of AI (H22), signaling that the complexity of AI technology is not a significant barrier and does not hinder students' AI practical application. Likewise, if students believe that they may achieve their expectations and goals, they may overcome technological complexity (Al-Adwan et al., 2022; Dervić et al., 2025). Technological complexity also depends on students' experience in AI use as well as types of AI tools. Lack of experience with AI and more complex technologies, such as machine learning platforms, may lead to a sense of technological complexity and act as a barrier to effective practical application of AI.

In contrast to other studies (Albayati, 2024; Alejandro et al., 2024; Kashive et al., 2020; Obenza et al., 2024) that demonstrated a significant relationship between attitudes and the intention to use ChatGPT and AI tools in general, our findings revealed an insignificant association between attitudes toward AI tools and their practical application (H23). This signifies that students hold neutral opinions, which neither hinder nor promote the practical application of AI. These neutral attitudes toward new technologies may stem from external factors such as a lack of institutional support, training, and accessibility (Ertmer et al., 2012), which significantly characterize the current context of our research. Furthermore, students' ability to quickly adapt to new technology (being digital natives), along with their habits and routines in using AI, may also account for the insignificant relationship between attitudes toward AI tools and their practical application. However, other factors—such as AI performance outcomes, user satisfaction, and even ethical considerations—have shown to have a significant positive impact on the practical application of AI. This suggests that while attitudes may not be a significant driving force, and students may have some reservations, they continue to use AI for their academic tasks.

Conclusion

The results indicated that the performance outcomes of AI use significantly influenced the perceived ease of use, the perceived usefulness, and the practical application of AI. This implies that when AI tools deliver impressive outcomes, students are more likely to perceive these tools as easy to use, useful, and applicable to their learning processes, prioritizing their functionality and effectiveness. The insignificant relationship between AI performance outcomes and attitudes and satisfaction with AI tools demonstrates that the emotional and affective dimensions of AI adoption are not determined by performance outcomes but by other factors, such as the perceived usefulness of AI tools, perceived ease of use, and the overall usability and utility of AI technology in students' learning processes.

Although there was an insignificant relationship between AI ethics, perceived ease of AI use, and perceived usefulness of AI, the relationship between AI ethics and the practical application of AI was significant. The results highlight that AI ethics does not predict students' perceptions of AI use but rather guides them in applying ethical standards and responsible use of AI responsibly while working on their school assignments. Furthermore, this emphasizes that AI ethics influence students' decisions regarding when and how to use AI tools in their learning processes.

The technological complexity of AI has significantly negatively impacted the perceived ease of using AI, highlighting that the increasing complexity of AI tools may present a critical barrier to student engagement in the AI adoption process. However, the technological complexity of AI has had an insignificant influence on the perceived usefulness of AI, attitudes towards AI use, student satisfaction with AI, and the practical application of AI, emphasizing that AI complexity does not diminish students' adoption and utilization of AI.

Nevertheless, the perceived ease of using AI significantly influenced both the perceived usefulness of AI and attitudes towards its use while having no significant impact on students' satisfaction with AI. This indicates that students find AI tools easy to use, consider them beneficial, and cultivate positive attitudes toward utilizing them. However, the lack of a significant relationship between the perceived usefulness of AI and students' satisfaction with it implies that their satisfaction is influenced by other factors, such as AI learning, the perceived usefulness of AI, and attitudes towards the use of AI.

The perceived usefulness of AI tools significantly influences students' attitudes and satisfaction with their use, underlining the critical role of AI's perceived usefulness in shaping these attitudes. This indicates that students recognize the value and benefits of utilizing AI-powered tools, feel that these tools fulfill their needs and expectations, and consider them practical and effective. All of these factors contribute to favorable attitudes, satisfaction, and, ultimately, the adoption of AI technology by students.

Similarly, attitudes toward AI use significantly predicted user satisfaction with AI, but they had an insignificant effect on the practical application of AI-powered tools. This underscores students' overall satisfaction with AI technology, indicating that positive attitudes are important predictors of students' satisfaction with AI tools and that such attitudes should be cultivated to enhance AI adoption. However, since attitudes toward AI tools are insignificant predictors of their practical implications, this suggests that attitudes alone are insufficient for effective AI integration in learning processes, and other factors should also be considered.

Students' satisfaction with AI-powered tools significantly predicts their practical application. This indicates that students are pleased with their AI experience, including the relevance of AI output, their expectations of AI tools, and usability. Consequently, this satisfaction positively influences the practical and meaningful use of AI-powered tools, particularly the adoption of AI technologies.

Ultimately, the findings of this study emphasize the need to enhance AI literacy among students by improving their comprehension, awareness, skills, knowledge, and competencies. This can be achieved by integrating AI applications into the curriculum and addressing potential risks to ensure the meaningful, effective, and ethical use and adoption of AI technology.

The study's contributions and implications for educational practice

This study conducted a thorough analysis of AI adoption among Austrian university students in teacher education programs. Consequently, the current quantitative and multidimensional research examined the interrelationship between AI ethics, attitudes toward using AI, AI learning, AI performance outcomes, AI technology complexity, and the perceived usefulness and ease of use of AI, along with AI user satisfaction and the practical application of AI. Its findings can be utilized by teachers, students, educational administrators, and policymakers to promote and enhance AI adoption and its meaningful, ethical, productive, and effective use. Additionally, these results may inform the design and redesign of AI tools to make them more functional, user-friendly, and focused on educational purposes, thereby reducing their adverse effects while improving AI's effectiveness, adoption, students' attitudes, satisfaction, and learning outcomes. Moreover, this study addresses the gap in the literature regarding AI adoption and use among university students in teacher education programs, particularly within the context of Austrian higher education.

As AI learning negatively affects the perceived usefulness of AI, the study suggests improving the functionality and design of AI tools and emphasizes the necessity for students to receive adequate training to use these tools effectively and ethically for academic purposes. This recommendation is supported by findings indicating that students' perceived ease of AI use is significantly negatively impacted by the technological complexity of AI. Moreover, technological complexity does not affect the perceived usefulness of AI tools, underscoring the importance of systematic training approaches to enable students to utilize AI technology effectively and meaningfully. Furthermore, the findings highlight the necessity of incorporating an ethical dimension into AI training as well as usage to foster its responsible adoption in educational environments.

Strategies for effective AI technology adoption should focus on simplifying their interfaces and enhancing usability while preserving the functionality that students already value. This is especially crucial for further AI technology integration in learning, as students with positive attitudes toward AI tools are more likely to engage deeply and explore various possibilities, potentially leading to numerous beneficial outcomes for future adoption, enhancement, and development of AI tools. Therefore, there is a need for AI design that achieves a better balance between simplicity and functionality, addressing students' behavioral, cognitive, and emotional engagement. This approach may result in improved, user-friendly designs and better interfaces, thus increasing the perceived value of AI-powered tools and encouraging greater adoption and more effective use among students.

The results indicate a significant positive effect of attitudes toward AI on overall satisfaction with AI-powered tools, suggesting that instructors should not only teach technical skills related to AI technology use but also foster positive attitudes to enhance students' AI experiences. However, attitudes alone do not significantly influence the practical application of AI technology, underscoring the need for approaches that address institutional support in infrastructure, attitudes, training, and AI implementation. Furthermore, student satisfaction with AI is a significant predictor of its practical use, implying that as students become more satisfied with their AI experiences, they are more likely to utilize and adopt AI tools for educational purposes. To ensure satisfaction with the AI experience, AI tools must function effectively, meeting students' expectations and needs while remaining relevant to their learning and user-friendly. This satisfaction should bridge AI perception with meaningful, practical applications and the adoption of AI technology. Moreover, to promote a more comprehensive, meaningful, ethical, and effective utilization of AI technology among students, AI developers, in partnership with educational institutions, including instructors, should prioritize the development of more functional, user-friendly AI tools and user-centered strategies that enhance student knowledge, skills, competencies, attitudes, and satisfaction, thereby facilitating ethical and effective AI adoption. Finally, since students in teacher education programs are future educators who will teach thousands of students, there is a need for appropriate policies, curricula, and effective training to develop their AI literacy skills. These should enable them to use AI-powered tools in a meaningful, effective, and ethical way. Such experiences and skills should serve as a solid foundation for their use of AI tools as future teachers and also help them effectively teach these literacies and skills to their students.

Limitations of the study and further research suggestions

Despite careful planning and a comprehensive research design, this study has limitations and provides suggestions for further investigation. Firstly, there are advantages and disadvantages to an online questionnaire. While contacting a large number of participants is more practical, online questionnaires tend to yield fewer responses than paper-and-pencil questionnaires (VanderStoep & Johnston, 2009). Moreover, rather than revealing their true feelings, opinions and experiences, respondents may provide socially desirable answers through self-reporting, including data collected through questionnaires (Richman et al., 1999). Future studies could employ various research methodologies, such as experimental designs, to test and compare the effectiveness of AI tools and their impact on students' learning outcomes. Additionally, a non-experimental comparative design could expose diverse student groups to a variety of assignments using different AI tools to assess various aspects of their experiences with AI.

Future research could involve a longitudinal design to assess the impacts of AI-powered tools adoption on various aspects of student learning, such as critical thinking, problem-solving, student engagement, and self-regulated learning. Furthermore, increasing the sample size, including instructors as participants, diversifying demographic factors, and utilizing alternative data collection techniques could enhance the study.

Future studies may further investigate how different types of training, infrastructure support, and enhanced AI design can mitigate the negative impact of technological complexity on AI adoption and broader, more comprehensive usage. In addition, further research may examine how AI ethics and trust influence students' behaviour patterns and the long-term adoption of AI-powered technology. Considering that this study was conducted within an Austrian tertiary education setting, future research could explore cross-national comparisons to assess the adoption and impact of AI in different educational environments.

Acknowledgements
The authors express gratitude to the colleagues who helped with data collection.

Author contributions
The first author (Senad Bećirović) conceived the study and led the conceptualization, designed and prepared the questionnaire, collected the data, developed the methodology, managed the software, performed data analysis, wrote the methodology, results, discussion, and conclusion sections, and thoroughly reviewed and edited the entire manuscript. The second author (Edda Polz) contributed to the study's conceptualization, assisted in questionnaire development, data collection, and preparation for analysis, and participated in the critical review and editing of the entire manuscript. The third author (Isabella Tinkel) contributed to the study's conceptualization, helped develop the questionnaire and collect data, authored the abstract, introduction, and literature review, and participated in reviewing and editing the full manuscript. All authors have reviewed and approved the manuscript.

Funding
No funds, grants, or other support were received.

Data availability
The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest
The authors declare that they have no conflicts of interest to disclose. They confirm that this work is original and has not been published elsewhere.

Received: 24 September 2025 Accepted: 16 November 2025
Published online: 25 November 2025

References

Ahn, H. Y. (2024). AI-powered e-learning for lifelong learners: IMPACT on performance and knowledge application. *Sustainability*. https://doi.org/10.3390/su16209066

Al Shamsi, J. H., Al-Emran, M., & Shaalan, K. (2022). Understanding key drivers affecting students' use of artificial intelligence-based voice assistants. *Education and Information Technologies, 27*(6), 8071–8091. https://doi.org/10.1007/s10639-022-10947-3

Al-Adwan, A. S., Yaseen, H., Alsoud, A., Abousweilem, F., & Al-Rahmi, W. M. (2022). Novel extension of the UTAUT model to understand continued usage intention of learning management systems: The role of learning tradition. *Education and Information Technologies, 27*(3), 3567–3593. https://doi.org/10.1007/s10639-021-10758-y

Albayati, H. (2024). Investigating undergraduate students' perceptions and awareness of using ChatGPT as a regular assistance tool: A user acceptance perspective study. *Computers and Education: Artificial Intelligence, 6*, 1–14. https://doi.org/10.1016/j.caeai.2024.100203

Alejandro, I. M., Sanchez, J. M., Sumalinog, G., Mananay, J., Goles, C., & Fernandez, C. (2024). Pre-service teachers' technology acceptance of artificial intelligence (AI) applications in education. *STEM Education, 4*, 445–465. https://doi.org/10.3934/steme.2024024

Almogren, A. S., Al-Rahmi, W. M., & Dahri, N. A. (2024). Exploring factors influencing the acceptance of ChatGPT in higher education: A smart education perspective. *Heliyon, 10*(11), e31887. https://doi.org/10.1016/j.heliyon.2024.e31887

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Asirit, L., & Hua, J. (2023). Converging perspectives: Assessing AI readiness and utilization in Philippine higher education. *Polaris Global Journal of Scholarly Research and Trends, 2*(3), 1–50. https://doi.org/10.58429/pgjsrt.v2n3a152

Ayanwale, M. A., & Molefi, R. R. (2024). Exploring intention of undergraduate students to embrace chatbots: From the vantage point of Lesotho. *International Journal of Educational Technology in Higher Education, 21*(1), 20. https://doi.org/10.1186/s41239-024-00451-8

Bandura, A., Freeman, W. H., & Lightsey, R. (1999). Self-efficacy: The exercise of control. *Journal of Cognitive Psychotherapy, 13*(2), 158–166. https://doi.org/10.1891/0889-8391.13.2.158

Barrett, A. J., Pack, A., & Quaid, E. D. (2021). Understanding learners' acceptance of high-immersion virtual reality systems: Insights from confirmatory and exploratory PLS-SEM analyses. *Computers & Education, 169*, 104214. https://doi.org/10.1016/j.compedu.2021.104214

Bation, N. D., & Pudan, J. C. (2024). Exploring the correlation between students' attitudes towards AI and their learning outcomes. *International Journal of Social Science and Human Research, 07*(02), 1243–1247. https://doi.org/10.47191/ijsshr/v7-i02-45

Bećirović, S. (2023a). Examining learning management system success: A multiperspective framework. *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-12308-0

Bećirović, S. (2023b). The relationship between cooperative learning, cultural intelligence, EFL motivation and students' performance: A structural equation modeling approach. *SAGE Open, 13*(4), 1–16. https://doi.org/10.1177/21582440231208975

Bećirović, S., Dervic, M., & Mattoš, B. (2025a). Exploring the factors affecting students' internet habits, self-efficacy in E-learning, and academic achievement: Structural equation modeling approach. *SAGE Open, 15*(2), 1–21. https://doi.org/10.1177/21582440251339286

Bećirović, S., & Mattoš, B. (2024). *Artificial Intelligence in the Transformation of Higher Education: Threats, Promises and Implementation Strategies* (pp. 23–43). https://doi.org/10.1108/978-1-83549-480-620241002

Bećirović, S., Polz, E., & Tinkel, I. (2025b). Exploring students' AI literacy and its effects on their AI output quality, self-efficacy, and academic performance. *Smart Learning Environments, 12*(1), 29. https://doi.org/10.1186/s40561-025-00384-3

Bilquise, G., Ibrahim, S., & Salhieh, S. M. (2024). Investigating student acceptance of an academic advising chatbot in higher education institutions. *Education and Information Technologies, 29*(5), 6357–6382. https://doi.org/10.1007/s10639-023-12076-x

Bozkurt, A. (2023). Unleashing the potential of generative AI, conversational agents and chatbots in educational praxis: A systematic review and bibliometric analysis of GenAI in education. *Open Praxis, 15*(4), 261–270. https://doi.org/10.55982/openpraxis.15.4.609

Brandhofer, G., & Tengler, K. (2024). Zur Akzeptanz von KI-Applikationen bei Lehrenden und Lehramtsstudierenden. *R & E-Source*. https://doi.org/10.53349/resource.2024.i3.a1277

Brew, M., Taylor, S., Lam, R., Havemann, L., & Nerantzi, C. (2023). *Towards Developing AI Literacy: Three Student Provocations on AI in Higher Education*. https://doi.org/10.5281/ZENODO.8032387

Bundeskanzleramt, BMK, Digital Austria, & AIM AT 2030. (2024). *Strategie der Bundesregierung für Künstliche Intelligenz Umsetzungsplan 2024*.

Cai, Q., Lin, Y., & Yu, Z. (2023). Factors influencing learner attitudes towards ChatGPT-assisted language learning in higher education. *International Journal of Human-Computer Interaction, 40*(22), 7112–7126. https://doi.org/10.1080/10447318.2023.2261725

Carmines, E. G., & McIver, J. P. (1981). Analyzing models with unobserved variables: Analysis of covariance structures. In G. W. Bohrnstedt & E. F. Borgatta (Eds.), *Social measurement: Current issues* (pp. 65–115). Sage.

Carolus, A., Koch, M. J., Straka, S., Latoschik, M. E., & Wienrich, C. (2023). MAILS - Meta AI literacy scale: Development and testing of an AI literacy questionnaire based on well-founded competency models and psychological

change- and meta-competencies. *Computers in Human Behavior: Artificial Humans, 1*(2), 100014. https://doi.org/10.1016/j.chbah.2023.100014
Chechitelli, A. (2023). *AI writing detection update from Turnitin's Chief Product Officer*. https://www.turnitin.com/blog/ai-writing-detection-update-from-turnitins-chief-product-officer
Chibisa, A., Sibaya, D. C., & Mutambara, D. (2022). Factors affecting pre-service teachers' acceptance of online learning to promote social distancing. *Progressio, 43*, 1–20. https://doi.org/10.25159/2663-5895/12229
Condie, R., & Livingston, K. (2007). Blending online learning with traditional approaches: Changing practices. *British Journal of Educational Technology, 38*(2), 337–348. https://doi.org/10.1111/j.1467-8535.2006.00630.x
Damnjanovic, V., Jednak, S., & Mijatovic, I. (2013). Factors affecting the effectiveness and use of Moodle: Students' perception. *Interactive Learning Environments, 23*(4), 496–514. https://doi.org/10.1080/10494820.2013.789062
Dautbašić, A., & Bećirović, S. (2022). Teacher and student experiences in online classes during COVID-19 pandemic in Serbia, Bosnia and Herzegovina and Croatia. *MAP Social Sciences, 2*(1), Article 1. https://doi.org/10.53880/2744-2454.2022.2.1.9
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008
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*(1), 18. https://doi.org/10.1186/s41239-024-00452-7
DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems, 19*(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748
Dervić, M., Bećirović, S., & Polz, E. (2025). Revolutionizing pedagogy: The transformative influence of artificial intelligence on educators' practices. In M. A. Adarkwah, S. Amponsah, R. Huang, & M. Thomas (Eds.), *Artificial intelligence and human agency in education: Volume one: Nexus between AI and human agency in educational contexts* (Vol. 1, pp. 193–212). Springer Nature.
Digital Austria. (2024). *Künstliche Intelligenz*. https://www.digitalaustria.gv.at/Themen/KI.html
Edgar, T. W., & Manz, D. O. (2017). Exploratory study. In T. W. Edgar & D. O. Manz (Eds.), *Research methods for cyber security* (pp. 95–130). Syngress. https://doi.org/10.1016/B978-0-12-805349-2.00004-2
Eraslan Yalcin, M., & Kutlu, B. (2019). Examination of students' acceptance of and intention to use learning management systems using extended TAM. *British Journal of Educational Technology, 50*(5), 2414–2432. https://doi.org/10.1111/bjet.12798
Ertmer, P. A., Ottenbreit-Leftwich, A. T., Sadik, O., Sendurur, E., & Sendurur, P. (2012). Teacher beliefs and technology integration practices: A critical relationship. *Computers & Education, 59*(2), 423–435. https://doi.org/10.1016/j.compedu.2012.02.001
Escobar-Rodriguez, T., & Monge-Lozano, P. (2012). The acceptance of Moodle technology by business administration students. *Computers & Education, 58*(4), 1085–1093. https://doi.org/10.1016/j.compedu.2011.11.012
Falebita, O. S., & Kok, P. J. (2024). Artificial intelligence tools usage: A structural equation modeling of undergraduates' technological readiness, self-efficacy and attitudes. *Journal for STEM Education Research*. https://doi.org/10.1007/s41979-024-00132-1
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104
Freeze, R., Alshare, K., Lane, P., & Wen, H. (2010). IS success model in E-learning context based on students' perceptions. *Journal of Information Systems Education, 21*(2), 173–184.
Grájeda, A., Burgos, J., Córdova, P., & Sanjinés, A. (2024). Assessing student-perceived impact of using artificial intelligence tools: Construction of a synthetic index of application in higher education. *Cogent Education, 11*(1), 2287917. https://doi.org/10.1080/2331186X.2023.2287917
Gross, C., Siepermann, M., & Lackes, R. (2020). The acceptance of smart home technology. In R. A. Buchmann, A. Polini, B. Johansson, & D. Karagiannis (Eds.), *Perspectives in business informatics research* (pp. 3–18). Springer International Publishing.
Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (Seventh edition, Pearson new international edition). Pearson Education Limited.
Hair, J., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd edition). Sage.
Hara, H., Takemura, A., & Yoshida, R. (2010). On connectivity of fibers with positive marginals in multiple logistic regression. *Journal of Multivariate Analysis, 101*(4), 909–925. https://doi.org/10.1016/j.jmva.2009.12.014
Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education. promise and implications for teaching and learning. The Center for Curriculum Redesign.
Holmes, W., Iniesto, F., Anastopoulou, S., & Boticario, J. G. (2023). Stakeholder perspectives on the ethics of AI in distance-based higher education. *The International Review of Research in Open and Distributed Learning, 24*(2), 96–117. https://doi.org/10.19173/irrodl.v24i2.6089
Hutson, J. (2024). Rethinking plagiarism in the era of generative AI. *Journal of Intelligent Communication*. https://doi.org/10.54963/jic.v4i1.220
Jang, Y., Choi, S., & Kim, H. (2022). Development and validation of an instrument to measure undergraduate students' attitudes toward the ethics of artificial intelligence (AT-EAI) and analysis of its difference by gender and experience of AI education. *Education and Information Technologies, 27*(8), 11635–11667. https://doi.org/10.1007/s10639-022-11086-5
Ji, H., Suo, L., & Chen, H. (2024). AI performance assessment in blended learning: Mechanisms and effects on students' continuous learning motivation. *Frontiers in Psychology, 15*, 1–11. https://doi.org/10.3389/fpsyg.2024.1447680
Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence, 1*(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2
Kanont, K., Pingmuang, P., Simasathien, T., Wisnuwong, S., Wiwatsiripong, B., Poonpirome, K., Songkram, N., & Khlaisang, J. (2024). Generative-AI, a learning assistant? Factors influencing Higher-Ed students' technology acceptance. *Electronic Journal of E-Learning, 22*(6), 18–33. https://doi.org/10.34190/ejel.22.6.3196

Kashive, N., Powale, L., & Kashive, K. (2020). Understanding user perception toward artificial intelligence (AI) enabled e-learning. *The International Journal of Information and Learning Technology, 38*(1), 1–19. https://doi.org/10.1108/IJILT-05-2020-0090

Khoso, F. J., Ali, N., & Aslam, N. (2023). Use of Chat-GPT and AI tools by undergraduates: Students and teachers' perspective. *Spry Contemporary Educational Practices, 2*(2), 339–362. https://doi.org/10.62681/sprypublishers.scep/2/2/14

Ko, Y.-H., & Leem, C.-S. (2021). The influence of AI technology acceptance and ethical awareness towards intention to use. *Journal of Digital Convergence, 19*(3), 217–225. https://doi.org/10.14400/JDC.2021.19.3.217

Kosiba, J. P. B., Odoom, R., Boateng, H., Twum, K. K., & Abdul-Hamid, I. K. (2022). Examining students' satisfaction with online learning during the Covid-19 pandemic—An extended UTAUT2 approach. *Journal of Further and Higher Education, 46*(7), 988–1005. https://doi.org/10.1080/0309877X.2022.2030687

Kraus, J., Scholz, D., Messner, E.-M., Messner, M., & Baumann, M. (2020). Scared to trust? – Predicting trust in highly automated driving by depressiveness, negative self-evaluations and state anxiety. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2019.02917

Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. *Review of Educational Research, 86*(1), 42–78. https://doi.org/10.3102/0034654315581420

Laupichler, M. C., Aster, A., Haverkamp, N., & Raupach, T. (2023). Development of the "Scale for the assessment of non-experts' AI literacy" – An exploratory factor analysis. *Computers in Human Behavior Reports, 12*, 100338. https://doi.org/10.1016/j.chbr.2023.100338

Lee, A. V. Y. (2024). Staying ahead with generative artificial intelligence for learning: Navigating challenges and opportunities with 5Ts and 3Rs. *Asia Pacific Journal of Education, 44*(1), 81–93. https://doi.org/10.1080/02188791.2024.2305171

Lepik, K. (2024). Trust, but verify: Students' reflections on using artificial intelligence in written assignments. In S. Kurbanoğlu, S. Špiranec, J. Boustany, Y. Ünal, İ Şencan, D. Kos, E. Grassian, D. Mizrachi, & L. Roy (Eds.), *Information experience and information literacy* (Vol. 2042, pp. 27–38). Springer Nature. https://doi.org/10.1007/978-3-031-53001-2_3

Li, L., Paudel, K. P., & Guo, J. (2021). Understanding Chinese farmers' participation behavior regarding vegetable traceability systems. *Food Control, 130*, 108325. https://doi.org/10.1016/j.foodcont.2021.108325

Liu, G., & Ma, C. (2024). Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model. *Innovation in Language Learning and Teaching, 18*(2), 125–138. https://doi.org/10.1080/17501229.2023.2240316

Ma, S., & Lei, L. (2024). The factors influencing teacher education students' willingness to adopt artificial intelligence technology for information-based teaching. *Asia Pacific Journal of Education*. https://doi.org/10.1080/02188791.2024.2305155

McCoy, R. T., Smolensky, P., Linzen, T., Gao, J., & Celikyilmaz, A. (2023). How much do language models copy from their training data? Evaluating linguistic novelty in text generation using RAVEN. *Transactions of the Association for Computational Linguistics, 11*, 652–670. https://doi.org/10.1162/tacl_a_00567

Memon, M., Ting, H., Cheah, J.-H., Ramayah, T., Chuah, F., & Cham, T.-H. (2020). Sample size for survey research: Review and recommendations. 4(2), i–xx. https://doi.org/10.47263/JASEM.4(2)01

Mohamed, K., Elkaimbillah, Z., & El Asri, B. (2024). Significance and impact of AI on pedagogical learning: a case study of moroccan students at the faculty of legal and economics. In Y. Farhaoui, A. Hussain, T. Saba, H. Taherdoost, & A. Verma (Eds.), *Artificial intelligence, data science and applications* (Vol. 838, pp. 124–129). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-48573-2_18

Montenegro-Rueda, M., Fernández-Cerero, J., Fernández-Batanero, J. M., & López-Meneses, E. (2023). Impact of the implementation of ChatGPT in education: A systematic review. *Computers*. https://doi.org/10.3390/computers12080153

More Women Than Men Study at Austrian Universities. (2023). Erudera. https://erudera.com/news/more-women-than-men-study-at-austrian-universities/

Moriuchi, E. (2019). Okay, Google!: An empirical study on voice assistants on consumer engagement and loyalty. *Psychology & Marketing, 36*(5), 489–501. https://doi.org/10.1002/mar.21192

Nja, C. O., Idiege, K. J., Uwe, U. E., Meremikwu, A. N., Ekon, E. E., Erim, C. M., Ukah, J. U., Eyo, E. O., Anari, M. I., & Cornelius-Ukpepi, B. U. (2023). Adoption of artificial intelligence in science teaching: From the vantage point of the African science teachers. *Smart Learning Environments, 10*(1), 1–19. https://doi.org/10.1186/s40561-023-00261-x

Obenza, B. N., Caballo, J. H. S., Caangay, R. B. R., Makigod, T. E. C., Almocera, S. M., Bayno, J. L. M., Camposano, J. J. R., Cena, S. J. G., Garcia, J. A. K., Labajo, B. F. M., & Tua, A. G. (2024). Analyzing university students' attitude and behavior toward AI using the extended unified theory of acceptance and use of technology model. *American Journal of Applied Statistics and Economics*. https://doi.org/10.54536/ajase.v3i1.2510

Odea, X., & Odea, M. (2023). Is Artificial Intelligence Really the Next Big Thing in Learning and Teaching in Higher Education? A Conceptual Paper. *Journal of University Teaching and Learning Practice*. https://doi.org/10.53761/1.20.5.06

Pinzolits, R. (2023). AI in academia: An overview of selected tools and their areas of application. *MAP Education and Humanities, 4*, 37–50. https://doi.org/10.53880/2744-2373.2023.4.37

Piotrkowicz, A., Wang, K., Hallam, J., & Dimitrova, V. (2021). Data-driven exploration of engagement with workplace-based assessment in the clinical skills domain. *International Journal of Artificial Intelligence in Education, 31*(4), 1022–1052. https://doi.org/10.1007/s40593-021-00264-0

Potter, K., Abill, R., & Louis, F. (2024a). The impact of artificial intelligence on students' learning experience (SSRN Scholarly Paper No. 4716747). https://doi.org/10.2139/ssrn.4716747

Potter, K., Abill, R., & Louis, F. (2024b). The impact of artificial intelligence on students' learning experience (SSRN Scholarly Paper No. 4716747). https://doi.org/10.2139/ssrn.4716747

Pratama, R. M. D., & Hastuti, D. P. (2024). The use of artificial intelligence to improve EFL students' writing skill. *English Learning Innovation, 5*(1), 13–25. https://doi.org/10.22219/englie.v5i1.30212

Prensky, M. (2001). Digital natives, digital immigrants Part 1. *On the Horizon, 9*(5), 1–6. https://doi.org/10.1108/10748120110424816

PricewaterhouseCoopers. (2023). PwC ChatGPT & KI-Studie: Fast zwei Drittel der Österreicher:innen sind für ein Verbot von ChatGPT an Schulen – jede:r Dritte fürchtet um Arbeitsplatz. PwC. https://www.pwc.at/de/presse/2023/chatgpt-ki.html

PricewaterhouseCoopers. (2024a). Hopes and Fears 2024. PwC. https://www.pwc.at/de/dienstleistungen/workforce-transformation/hopes-and-fears-2024.html
PricewaterhouseCoopers. (2024b). PwC Studie: Mehrheit der Konsument:innen über KI-Entwicklung besorgt. PwC. https://www.pwc.at/de/presse/2024/mehrheit-der-konsumentinnen-ueber-ki-entwicklung-besorgt.html
Raykov, T., & Marcoulides, G. A. (2008). *An introduction to applied multivariate analysis*. Routledge. https://doi.org/10.4324/9780203809532
Richman, W. L., Kiesler, S., Weisband, S., & Drasgow, F. (1999). A meta-analytic study of social desirability distortion in computer-administered questionnaires, traditional questionnaires, and interviews. *Journal of Applied Psychology, 84*(5), 754–775. https://doi.org/10.1037/0021-9010.84.5.754
Rokhman, F., Mukhibad, H., Bagas Hapsoro, B., & Nurkhin, A. (2022). E-learning evaluation during the COVID-19 pandemic era based on the updated of Delone and McLean information systems success model. *Cogent Education, 9*(1), 1–25. https://doi.org/10.1080/2331186X.2022.2093490
Saavedra, Á., Chocarro, R., Cortiñas, M., & Rubio, N. (2023). Impact of process and outcome quality on intention for continued use of voice assistants. *Spanish Journal of Marketing-ESIC, 28*(4), 402–419. https://doi.org/10.1108/SJME-12-2022-0251
Sargın, S. (2024). Antecedents and consequences of consumers' attitudes towards artificial intelligence in social media. *Business and Economics Research Journal, 15*(3), 229–256. https://doi.org/10.20409/berj.2024.443
Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education, 21*(1), 46. https://doi.org/10.1186/s41239-024-00478-x
Shanto, S. S., Ahmed, Z., & Jony, A. I. (2024). Enriching learning process with generative AI: A proposed framework to cultivate critical thinking in higher education using chat GPT. 45(1).
Soodan, V., Rana, A., Jain, A., & Sharma, D. (2024). AI chatbot adoption in academia: Task fit, usefulness and collegial ties. *Journal of Information Technology Education: Innovations in Practice, 23*, 001. https://doi.org/10.28945/5260
Stracke, C. M., Griffiths, D., Pappa, D., Bećirović, S., Polz, E., Perla, L., Grassi, A. D., Massaro, S., Skenduli, M. P., Burgos, D., Punzo, V., Amram, D., Ziouvelou, X., Katsamori, D., Gabriel, S., Nahar, N., Schleiss, J., & Hollins, P. (2025a). Analysis of artificial intelligence policies for higher education in Europe. *International Journal of Interactive Multimedia and Artificial Intelligence, 9*, 124–137. https://doi.org/10.9781/ijimai.2025.02.011
Stracke, C. M., Nahar, N., Punzo, V., Massaro, S., Pappa, D., Grassi, A. D., Bećirović, S., Hollins, P., Ziouvelou, X., Skenduli, M. P., & Burgos, D. (2025b). Artificial intelligence policies for higher education: Manifesto for critical considerations and a roadmap. *MAP Education and Humanities, 6*, 61–73. https://doi.org/10.53880/2744-2373.2025.6.61
Teo, T. (2009). Modelling technology acceptance in education: A study of pre-service teachers. *Computers & Education, 52*(2), 302–312. https://doi.org/10.1016/j.compedu.2008.08.006
Toros, E., Asiksoy, G., & Sürücü, L. (2024). Refreshment students' perceived usefulness and attitudes towards using technology: A moderated mediation model. *Humanities and Social Sciences Communications, 11*(1), 1–10. https://doi.org/10.1057/s41599-024-02839-3
VanderStoep, S. W., & Johnston, D. D. (2009). *Research methods for everyday life: Blending qualitative and quantitative approaches* (1st ed). Jossey-Bass.
Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x
Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540
Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*, 157–178. https://doi.org/10.2307/41410412
Wang, B., Rau, P.-L.P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology, 42*(9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768
Woo, D. J., Susanto, H., Yeung, C. H., Guo, K., & Fung, A. K. Y. (2024). Exploring AI-generated text in student writing: How does AI help? *Language Learning*. https://doi.org/10.64152/10125/73577
Xing, J., & Jiang, Q. (2024). Factors influencing user experience in AI chat systems – a satisfaction study based on factor analysis and linear regression. *Kybernetes*. https://doi.org/10.1108/K-10-2023-2237
Yew, W. C., Kong, S. M., Awang, A. H., & Yi, G. R. (2022). Developing a conceptual model for the causal effects of outdoor play in preschools using PLS-SEM. *Sustainability, 14*(6), 6. https://doi.org/10.3390/su14063365
Yildiz Durak, H. (2023). Conversational agent-based guidance: Examining the effect of chatbot usage frequency and satisfaction on visual design self-efficacy, engagement, satisfaction, and learner autonomy. *Education and Information Technologies, 28*(1), 471–488. https://doi.org/10.1007/s10639-022-11149-7
Yu, C., Yan, J., & Cai, N. (2024). ChatGPT in higher education: Factors influencing ChatGPT user satisfaction and continued use intention. *Frontiers in Education, 9*, 1–11. https://doi.org/10.3389/feduc.2024.1354929
Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: A multigroup analysis. *International Journal of Educational Technology in Higher Education, 20*(1), 49. https://doi.org/10.1186/s41239-023-00420-7
Zindela, N. (2023). Comparing measures of syntactic and lexical complexity in Artificial Intelligence and L2 human-generated argumentative essays. *International Journal of Education and Development Using Information and Communication Technology (IJEDICT), 19*(3), 50–68.

Publisher's Note