Education and Information Technologies
https://doi.org/10.1007/s10639-024-12916-4

The acceptance of artificial intelligence in education among postgraduate students in Malaysia

Fahmi Zaidi Abdul Razak[2] · **Mohd Amli Abdullah**[1] · **Badli Esham Ahmad**[3] · **Wan Hashridz Rizal Bin Wan Abu Bakar**[2] · **Nur Aulia Fahada Binti Misaridin**[2]

Received: 13 September 2023 / Accepted: 18 July 2024

Abstract

The utilization of artificial intelligence (AI) among students is rapidly gaining prominence worldwide. However, Malaysia lags in terms of research and information in this area. This quantitative study aims to identify the factors that contribute to the adoption of AI among postgraduate students. The study focuses on the postgraduate student population in Malaysia, employing convenience sampling techniques. The research findings reveal that two variables, namely hedonistic and habit, significantly influence the adoption of AI among postgraduate students. These findings are expected to provide valuable insights to stakeholders for future implementation of AI among postgraduate students. By understanding the key factors influencing AI adoption, relevant parties can effectively strategize and enhance the utilization of AI technology in the postgraduate education landscape.

Keywords Artificial intelligence · Postgraduate students · Partial least squares · Unified Theory of Acceptance and Use of Technology 2

✉ Mohd Amli Abdullah
amli_baharum@uitm.edu.my

Fahmi Zaidi Abdul Razak
fahmizaidirazak@gmail.com

Badli Esham Ahmad
badli@uitm.edu.my

Wan Hashridz Rizal Bin Wan Abu Bakar
rizal@unipsas.edu.my

Nur Aulia Fahada Binti Misaridin
fahada@unipsas.edu.my

[1] Faculty of Business & Management, Universiti Teknologi MARA Cawangan Pahang, Jengka Campus, Bandar Tun Abdul Razak, 26400 Jengka, Pahang, Malaysia

[2] Universiti Islam Pahang Sultan Ahmad Shah, 25200 Kuantan, Pahang, Malaysia

[3] Academy of Language Studies, Universiti Teknologi MARA Cawangan Pahang, Jengka Campus, Bandar Tun Abdul Razak Jengka, 26400 Jengka, Pahang, Malaysia

Published online: 06 August 2024

1 Introduction

As of 2023, the definitions of Artificial Intelligence (AI) have evolved with the advancement of technology and research. One definition of AI is "the use of machine learning and deep learning techniques to enable computers to perform tasks that would typically require human intelligence, such as recognizing images and natural language processing" (Bengio et al., 2021). This definition emphasizes the importance of machine learning and deep learning in AI, which are methods that allow machines to learn from data and improve their performance over time. Another study defined AI as "the science and engineering of making intelligent machines, especially intelligent computer programs" (McCarthy, 2007). This definition highlights the focus of AI on creating intelligent machines and computer programs that can perform tasks typically associated with human intelligence. Artificial intelligence (AI) is a technology that involves the development of intelligent machines capable of performing tasks that typically require human intelligence. In the context of technology, AI refers to the use of algorithms and computational models to simulate human intelligence and perform tasks such as speech recognition, image processing, natural language processing, and decision-making. AI technologies can provide personalized learning experiences, identify students' strengths and weaknesses, and offer targeted interventions to support their learning progress (Yang et al., 2020). In summary, these definitions highlight the focus of AI on creating intelligent machines and computer programs, the importance of machine learning and deep learning in AI, and the idea that AI systems can learn from data and improve their performance over time.

The use of Artificial Intelligence (AI) in education has been gaining traction in recent years. One area where AI has been applied is in personalized learning, where AI systems can tailor learning experiences to the needs and abilities of individual students. The integration of AI in education has the potential to enhance student engagement, improve learning outcomes, and promote critical thinking and problem-solving skills (Puspitaningsih et al., 2022). For example, AI-powered educational robots can engage students in interactive and immersive learning experiences, fostering their creativity and collaboration skills (Yang et al., 2020). Pane et al. (2014) also give an example that an AI-powered platform called Carnegie Learning has been used in schools to provide personalized math instruction, and studies have shown that it can improve student achievement (Pane et al., 2014).

The objective of this study is to ascertain the key factors that contribute to the acceptance of artificial intelligence technology among postgraduate students in Malaysia.

1.1 Issues in the introduction of AI

The use of AI raises ethical concerns and challenges related to the interaction between humans and machines. Biliavska et al. (2022) highlight the distinction between human beings and machines, emphasizing the need to consider the ethical implications of AI. Additionally, Luo et al. (2020) discuss the caveats associated with using AI coaches for sales agents, including the importance of human managers in providing interpersonal communication skills and addressing information overload problems. These issues highlight the ethical considerations and challenges in integrating AI into human-centric domains. Murdick et al. (2020) emphasize the need for viable definitions and categorizations of AI to address security and economic implications. Popovič and Sábo (2021) specifically focus on the problem of defining AI and robots for tax purposes, highlighting the challenges in creating clear and comprehensive definitions. These challenges in defining and categorizing AI have implications for policymaking, regulation, and taxation. Another issue is the use of AI can have both positive and negative impacts on community well-being and performance. Musikanski et al. (2020) propose research on the nexus of community well-being and AI, highlighting the need to measure the impacts of AI on well-being and develop interventions to safeguard or improve community well-being. Ahmad et al. (2022) discuss the barriers and challenges faced by manufacturing firms in implementing AI, such as the lack of talent and incentives. These issues demonstrate the potential impact of AI on community well-being and the challenges in harnessing its benefits effectively. These three main issues encompass the ethical considerations and human–machine interaction challenges, the need for clear definitions and categorizations of AI, and the impact of AI on community well-being and performance. Addressing these issues is crucial for responsible and effective implementation of AI technologies in various domains.

The use of artificial intelligence (AI) in education presents several challenges and issues. One of the primary challenges is the limited research and understanding of the current applications and effectiveness of AI in education (Chan & Zary, 2019). Despite the rapid advancements of AI, education has not kept pace with its developments, leading to limited adoption of AI teaching in education (Lee et al., 2021). Additionally, there is a need to integrate AI literacy into the school curriculum, but there are concerns about the lack of digitalization and the sensitive nature of examinations (Wood et al., 2021). Another challenge is the ethical concerns associated with the use of AI in education. The rapid advancement of AI technologies in education, while having the potential to revolutionize educational styles, also brings ethical concerns regarding pedagogical issues, data integrity, interpretability, utilitarianism, and more that need careful consideration (Yu & Yu, 2023). Furthermore, the integration of AI into technology education faces challenges related to curriculum development and AI ethics. The development of AI education standards, such as the "5 big ideas in AI," highlights the need to incorporate AI ethics and core AI concepts into the curriculum (Kwon, 2023). However, the multifactorial and situational nature of ethical issues can limit the use of AI in certain contexts, and the importance of empathy in medical education cannot be overlooked (Chan & Zary, 2019). Lack of understanding also becomes a challenge among educators about how to use AI effectively. Many educators may not have the necessary technical expertise to use AI in their teaching and may be hesitant to incorporate new technologies into their classrooms (Zawacki-Richter et al., 2019). Furthermore, the adoption of AI in education can be costly, and many schools and educational institutions may not have the resources to invest in AI technologies.

Higher education also faces several issues and challenges in the use of artificial intelligence (AI). The introduction of AI in higher education brings both advantages and disadvantages, and it is important to carefully consider the potential benefits and drawbacks (Asatryan & Matevosyan, 2023). Challenges in AI adoption in higher education include the limited understanding of its impacts, the potential to exacerbate inequalities and a lack of key features needed to promote equity and inclusion, emphasizing the need for further research in this area (Lainjo & Tsmouche, 2023). Understanding students' perspectives and ensuring their acceptance of AI-based technologies is essential for successful integration into higher education (Watanabe, 2023). A study by Seo et al. (2021), adopting AI systems in online learning lies in their impact on learner-instructor interaction, with potential effects on communication, support, presence, and concerns regarding surveillance, privacy, and social boundaries.

The integration of AI in higher education assessments prompts inquiries about language proficiency, critical analysis, AI-generated responses' structure and relevance, and the ethical use of AI language models like ChatGPT in academic assignments, underlining the evolving landscape of higher education (Tenakwah et al., 2023). It is crucial to address these challenges and ensure that the integration of AI in higher education promotes equity and inclusivity. Additionally, there is a need for more research on students' acceptance and opinions of AI-based systems in higher education (Watanabe, 2023). Moreover, there is limited literature on the effects of AI on higher learning, and this topic remains substantially underexplored (Lainjo & Tsmouche, 2023). So, it is important to note that the application of AI in higher education is still limited and not widespread (Lucena et al., 2019).

1.2 Artificial Intelligence (AI) in higher education

The integration of Artificial Intelligence (AI) in education has become increasingly important in recent years. One reason for this is the potential of AI to improve student learning outcomes. Additionally, AI can help identify areas where students may be struggling and provide targeted interventions to support their learning. Another important aspect of AI in education is its ability to automate time-consuming tasks for educators. AI systems can grade assignments, provide feedback, and even design personalized lesson plans, freeing up teachers to focus on more creative and interactive aspects of teaching (Zawacki-Richter et al., 2019). This can help reduce teacher workload and increase the amount of time teachers can spend engaging with their students. Okunlaya et al. (2022) highlight the essential effect of AI on education and personalized learning in research institutions. They mention that AI has changed the tools for carrying out research and has implications for data collection, visualization, modelling, and communication. Kwon (2023) discusses the implementation of AI in technology education for middle school students. The research results have implications for integrating AI into technology education. Leander and Burriss (2020) address the benefits and complications of AI in the realm of learning analytics tools. They highlight the gap between the realities of AI and current educational curricula, practices, and theories.

The use of artificial intelligence (AI) in higher education, an emerging technology with the potential to revolutionize teaching and learning processes, has garnered significant attention and a growing interest with worldwide recognition of its importance in recent years (Lucena et al., 2019) (Bozkurt et al., 2021). It has the potential to revolutionize teaching and learning processes, offering numerous benefits such as efficiency, personalization, and effectiveness (Bozkurt et al., 2021). AI has been applied in education, encompassing adaptive learning, teaching evaluation, and virtual classrooms, to enhance teaching quality and improve students' learning experiences, showing promising results (Huang et al., 2021). It is also supported by another study where AI technologies, such as adaptive learning, assessment and evaluation, intelligent tutoring systems, and personalized learning, have been applied in education to enhance teaching quality, improve learning outcomes, and provide tailored educational experiences for students (Bozkurt et al., 2021; Kwon, 2023). Overall, the use of AI in the education industry has the potential to revolutionize teaching and learning, improve educational outcomes, and create more personalized and engaging learning experiences for students (Akgun & Greenhow, 2021; Bozkurt et al., 2021; Huang et al., 2021).

1.3 Artificial intelligence in postgraduate education

Artificial Intelligence (AI) is increasingly being utilized in postgraduate education to enhance various aspects of learning and academic performance. Studies have shown that AI-powered tools, such as digital writing assistants, can effectively support non-native postgraduate students in improving their academic writing skills through formative feedback and assessment Nazari et al. (2021). Moreover, studies have examined the use of AI tools, such as ChatGPT, in enhancing English major students' discourse writing performance and conversational skills, indicating the potential value of AI technologies in language instruction (Wu, 2024; Chauke et al., 2024). Postgraduate students' perceptions of AI tools, particularly ChatGPT, have been explored to understand the benefits associated with AI utilization in academic success (Chauke et al., 2024).

The study of Artificial Intelligence (AI) in postgraduate education is essential for various reasons. Firstly, AI technologies have the potential to enhance the educational experience of postgraduate students by providing personalized learning experiences tailored to individual needs Wu (2024). This personalized approach can lead to improved learning outcomes and academic success (Chauke et al., 2024). Additionally, the integration of AI in postgraduate education can help students develop critical skills such as data interpretation, algorithmic understanding, and communication of AI-based solutions, which are increasingly important in various fields of study (Chai et al., 2022). Moreover, AI in postgraduate education can contribute to the development of future professionals who are proficient in utilizing AI ethically and responsibly in their respective fields (Omorogiuwa et al., 2023). By incorporating AI tools and technologies into postgraduate curricula, students can gain valuable experience in working with AI systems, preparing them for the evolving demands of the workforce (Tominc & Rožman, 2023). Furthermore, AI education can empower postgraduate students to leverage AI for research, innovation, and problem-solving in their academic pursuits (Huang et al., 2016). Furthermore, the study of AI on postgraduate students is essential for fostering innovation and entrepreneurship among students (Ou & Si, 2014). AI education can help students cultivate an innovative spirit, enhance problem-solving skills, and drive entrepreneurial behaviour, equipping them with the tools needed to thrive in a rapidly changing technological landscape. Additionally, AI education can contribute to the quality monitoring and assurance of postgraduate education, ensuring that students receive a high standard of education and training (Huang et al., 2016; Huangfu, 2023).

1.4 Unified theory of acceptance and use of technology (UTAUT) theory

The Unified Theory of Acceptance and Use of Technology (UTAUT), widely recognized and extensively used in information systems and other disciplines, offers a comprehensive framework encompassing factors like performance expectancy, effort expectancy, social influence, and facilitating conditions to understand individuals' acceptance and use of technology (Venkatesh et al., 2016). (Fig. 1). UTAUT has been applied and validated across different systems and contexts, demonstrating its robustness and applicability (Liu et al., 2021). The significance of UTAUT extends to providing insights into individuals' technology acceptance and use across various industries, including education, offering a framework to understand factors influencing students' and educators' adoption of educational technologies, which is essential for their successful implementation. UTAUT's consideration of factors like performance expectancy, effort expectancy, and social influence aids in

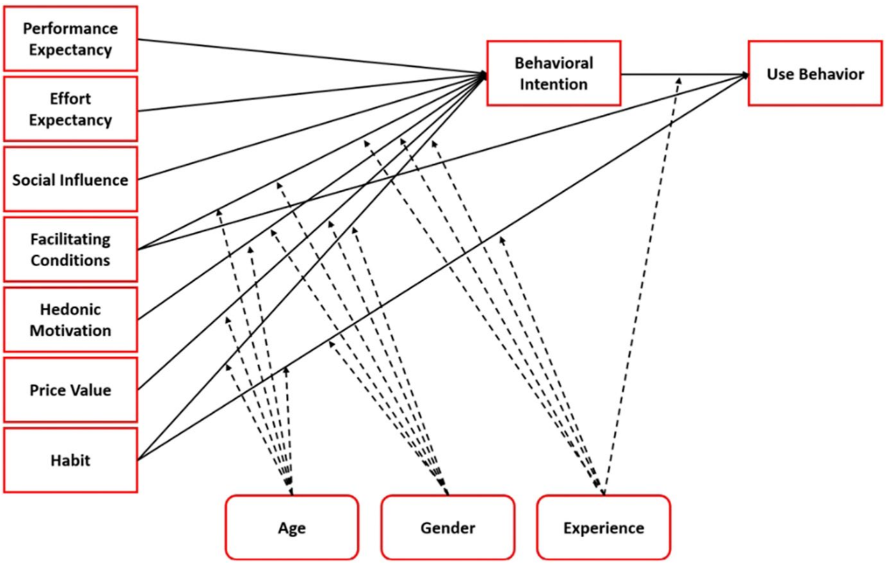

Fig. 1 Unified Theory of Acceptance and Use of Technology (UTAUT) theory

identifying determinants of technology acceptance and guides the design of technology-enhanced learning environments (Yawised et al., 2022).

UTAUT2 incorporates several factors that influence technology acceptance, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) (Ayensa et al., 2016). In UTAUT2, factors such as PE (perceived benefits and usefulness), EE (perceived ease of use), SI (social influence), and FC (availability of resources and support) collectively influence individuals' Behavioural Intention (BI) to use technology, which, in turn, mediates their Use Behaviour (UB) (Ayensa et al., 2016). Effort Expectancy (EE) in the UTAUT2 model relates to individuals' perception of the ease of use and effort required for a specific technology, reflecting their belief in the technology's ease of use; a higher level of effort expectancy indicates the technology is perceived as easy to use, positively influencing adoption intentions (Dakduk et al., 2018). Hedonistic Experiences (HE) in the UTAUT2 model represent the enjoyment and pleasure individuals derive from technology use, adding an emotional dimension to the acceptance process, and significantly influencing their attitudes and intentions toward technology adoption (Azizi et al., 2020). Habit (HA) in the UTAUT2 model signifies individuals' automatic and routine behaviours of using technology, reflecting the degree to which they have incorporated technology into their daily routines; this habitual use reduces the cognitive effort needed for adoption and enhances the likelihood of continued use (Azizi et al., 2020). Habit acts as a reinforcing factor that strengthens individuals' intentions and behaviours toward technology use. These factors, namely Effort Expectancy, Hedonistic Experiences, and Habit are important components of the UTAUT2 model that contribute to understanding individuals' acceptance and use of technology. They provide insights into individuals' perceptions of ease of use, enjoyment, and habitual behaviours, which influence their intentions and behaviours toward technology adoption and use (Azizi et al., 2020; Seo, 2020). By considering these factors, researchers and practitioners can design interventions and strategies to enhance technology acceptance and utilization in various contexts.

1.5 Hypothesis development

1.5.1 Performance expectancy

According to Venkatesh et al. (2012b), performance expectancy pertains to the degree to which individuals perceive that utilizing technology will offer benefits in accomplishing specific tasks or activities. Furthermore, Chan et al. (2022), noted that performance expectancy directly influences consumers' intention to use Open Banking. Similarly, the study conducted by Alomari and Abdullah (2023) revealed a positive impact of performance expectancy on the behavioural intention to use Cryptocurrency. Consequently, we propose the following hypothesis:

> H[1]: Performance expectancy is positively related to the intention to use artificial intelligence

1.5.2 Effort expectancy

Effort expectancy, as defined by Venkatesh et al. (2012b), pertains to the perceived level of ease associated with consumers' use of technology. Several studies, such as the research conducted by Rahi et al. (2019), have examined the relationship between effort expectancy and the intention to adopt and use various technologies. Rahi et al. (2019) specifically found a positive association between effort expectancy and the user's intention to adopt Internet banking. Drawing upon these aforementioned studies, it can be concluded that:

> H^2: Effort expectancy is positively related to the intention to use artificial intelligence

1.5.3 Social influences

Based on the research conducted by various scholars, social influence refers to the extent to which individuals perceive that important others believe they should use a new system (Venkatesh et al., 2003). Cokins et al. (2020) conducted a study showing that social influence positively influences the intention to use online accounting platforms. Huang (2020) found that social influence directly affects the continuance intention to use social mindtools. Koul and Eydgahi (2020) discovered significant positive relationships between social influence, the perceived safety of autonomous vehicle technology, and the intention to use autonomous vehicles. Zhou (2022) identified three social influence factors, namely subjective norm, social identity, and group norm, that influence users' sharing intention. In addition, Goli and Khan (2022) found that perceived enjoyment, social influence, and narcissism have a positive impact on users' intention to use the TikTok app. Khalid et al. (2021) conducted a study and found that social influence, absorptive capacity, facilitating conditions, and perceived autonomy significantly influence students' intention to use Massive Open Online Courses (MOOCs) in Thailand and Pakistan. Lastly, Chen et al. (2023) discovered that students' self-efficacy, social influence, and motivation for knowledge sharing influence the continuance intention to use Problem-Based Learning (PBL). Based on these findings, we propose the following hypothesis:

> H^3: Social influence is positively related to the intention to use artificial intelligence

1.5.4 Facilitating condition

Based on the research conducted by various scholars, facilitating conditions play a crucial role in determining individuals' intentions to use different systems and technologies. Venkatesh et al. (2003) define facilitating conditions as the belief individuals hold regarding the presence of organizational and technical infrastructure that supports system usage. Afrizal and Wallang, (2021) found that constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT), such as performance expectancy, effort expectancy, social influence, and facilitating conditions, are important factors influencing citizens' intentions to use e-government. Gharaibeh et al. (2021) also discovered that facilitating conditions significantly impact the intention to use Mobile Augmented Reality in Tourism (MART). Furthermore, Zhou et al. (2021) observed that facilitating conditions are related to the intention to use live e-commerce shopping. Additionally, Wang et al. (2020) conducted a study that revealed the influence of facilitating conditions on students' intentions to use business simulation games. Based on this information, we propose the following hypothesis:

> H^4: Facilitating condition is positively related to the intention to use artificial intelligence

1.5.5 Hedonistic

Hedonistic is referring to Hedonic motivation is defined as the fun or pleasure derived from using a technology (Venkatesh et al., 2012b). A study by (Wang et al., 2020) found that hedonistic influences students' intention to use business simulation games. A study by (Ashraf et al., 2019) found that hedonic value influences the continuance intention to use social media in China. A study by (Yang et al., 2022) found that hedonic value influence college students' intention to use metaverse technology for basketball learning. We hypothesized that:

> H^5: Hedonistic is positively related to the intention to use artificial intelligence

1.5.6 Habit

Drawing upon the research conducted by several scholars, habit refers to the degree to which individuals perform behaviours automatically based on prior learning (Limayem et al., 2007). Yang et al. (2022) conducted a study demonstrating that habit influences college students' intentions to use metaverse technology for basketball learning. Foroughi et al. (2023) found that habit strongly determines the intention to continue using gamification applications for task management. Additionally, Khayer et al., (2023) employed structural equation modelling and confirmed that satisfaction, perceived usefulness, perceived enjoyment, habit, and context are significant predictors of continuance intention. Moreover, Walle et al. (2023) discovered a positive direct relationship between habit and the intention to use wearable health devices. Based on these findings, we can conclude that:

> H^6: Habit is positively related to the intention to use artificial intelligence

2 Methodology

The objective of this study is to explore the impact of content quality on user satisfaction. To accomplish this objective, a quantitative research design was employed, utilizing cross-sectional data collection and a survey questionnaire as the primary research instrument. The survey utilized a 5-point Likert scale to measure responses, with "strongly disagree" (1) and "strongly agree" (5) as the two endpoints of the scale. Convenience sampling was utilized to collect data, given the absence of a comprehensive sampling frame. A total of 500 questionnaires were distributed, with only 315 being deemed eligible for analysis. These data collection techniques and sample size were chosen to ensure the highest levels of validity and reliability for this study. During the process of data collection, participants were given a comprehensive briefing on the aims and objectives of the study. This served as an opportunity to clarify any doubts they may have had about the research. In addition, the confidentiality of the study data was emphasized, with the participants being made aware that the information collected would be used solely for research purposes. This was done to ensure that their privacy and confidentiality were maintained at all times and to encourage honest and accurate responses. The collected data was analysed using SPSS 22. The study employs two types of analyses: descriptive analysis and inference for descriptive analysis. The researchers used SPSS software to analyse the mean, standard deviation, and percentage to explore and describe the variables in the study model. Additionally, Smart PLS software was used to test the validity and reliability of the research model before testing the research hypothesis. The use of SPSS and Smart PLS software allowed for a comprehensive analysis of the data, helping the researchers to draw meaningful conclusions from the study.

2.1 Data analysis

In this study, we employed structural equation modelling (SEM) to evaluate both the measurement and structural models. Specifically, we adopted the component-based partial least squares (PLS) approach, which is widely used for assessing measurement scales and testing research hypotheses. The choice to employ the PLS-SEM (Partial Least Squares Structural Equation Modelling) approach for data analysis in our study was driven by the recommendations of Hair et al. (2011). Hair suggests that PLS-SEM is particularly well-suited for researchers seeking to develop and refine theories in their study. By opting for PLS-SEM, we aim to comprehensively capture the intricate relationships within our research model and derive valuable insights to advance theory development. The initial step involves the data filtering process, which entails the identification and removal of problematic data points, such as missing values and outliers. Following the completion of the filtering process, the researcher proceeds to evaluate the validity and reliability of the research instrument to ensure its accuracy and consistency. Following the guidelines proposed by Hair et al. (2014), it is essential to evaluate the research model from both the measurement model and structural model perspectives.

2.2 Measurement model assessment

In the measurement model, it is essential to perform several assessments as proposed by Benitez et al., (2020) such as comprehensive instrument validity testing, which encompasses evaluations of convergent validity and discriminant validity. These critical assessments enable researchers to ensure the reliability and accuracy

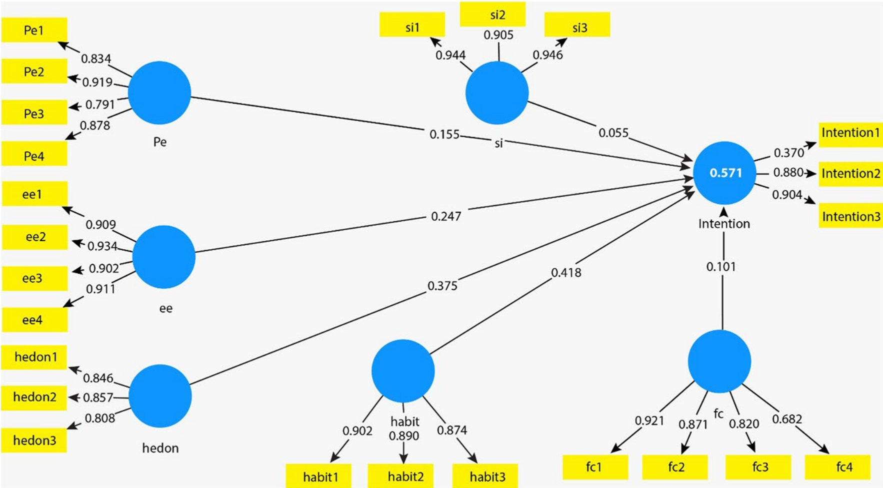

Fig. 2 PLS algorithm

of the research instrument by examining the degree to which the constructs within the instrument are conceptually distinct and exhibit minimal overlap. By conducting thorough validity testing procedures, we ensure the strength and reliability of our research instrument, thereby enhancing the validity and credibility of our finding.

The factor loadings in the measurement model range from 0.79 to 0.94, which aligns with the criteria set by Hair et al. (2021). These loadings indicate a strong relationship between the observed indicators and their corresponding latent constructs. Furthermore, the internal consistency of the measurement scales, Cronbach's alpha value, falls within the range of 0.70 to 0.98, meeting the criteria proposed by (Hair et al., 2020). Figure 2 and Table 1 depict the output of the SmartPLS software, illustrating the findings of the instrument's convergent validity analysis.

On the evaluation of discriminant validity, multiple assessment methods, including the Fornell and Larcker criterion, HTMT, and cross-loading, were employed (see Table 2, Table 3, Fig. 3 and Table 4). While all evaluation aspects demonstrate satisfactory adherence to the discriminant validity criteria, the HTMT value failed to meet the predetermined threshold. To ensure compliance with the established criteria, it became imperative to selectively remove certain items, namely the "hedon 3" and "fc4" components. Remarkably, once these items were eliminated, the HTMT value notably improved, thereby enhancing the overall measure of discriminant validity.

2.3 Structural model assessment

Benitez et al. (2020) state that the evaluation of the structural model entails assessing various aspects, including the overall fit of the estimated model, the significance and strength of path coefficient estimates, the effect sizes (f^2), and the coefficient

Table 1 Measurement quality

Items	Factor loadings	Cronbach alpha	Composite reliability(rho_a)	Composite reliability(rho_c)	Average variance extracted (AVE)
Pe1	0.834	0.879	0.893	0.917	0.734
Pe2	0.919				
Pe3	0.791				
Pe4	0.878				
Ee1	0.909	0.935	0.944	0.953	0.836
Ee2	0.934				
Ee3	0.902				
Ee4	0.911				
Fc1	0.936	0.882	0.922	0.926	0.808
Fc2	0.913				
Fc3	0.844				
Habit1	0.902	0.867	0.871	0.919	0.790
Habit2	0.890				
Habit3	0.874				
Hedon1	0.939	0.854	0.858	0.932	0.872
Hedon2	0.929				
Intention1	0.870	0.861	0.862	0.915	0.783
Intention2	0.880				
Intention3	0.904				
Si1	0.944	0.924	0.932	0.952	0.868
Si2	0.905				
Si3	0.946				

of determination (R^2). A summary of the steps involved in evaluating the structural model can be found in Table 5.

Table 5 provides important insights into the relationship between different factors and the intention to adopt artificial intelligence (AI) in education among postgraduate students in Malaysia. The findings contribute to our understanding of the factors influencing AI adoption in educational settings.

To determine the value of the path coefficient, researchers commonly employ the Partial Least Squares (PLS) algorithm procedure. By utilizing the PLS algorithm,

Table 2 Heterotrait-monotrait (HTMT) ratio

	Pe	Ee	Fc	Habit	Hedon	Intention	Si
Pe							
Ee	0.758						
Fc	0.737	0.868					
Habit	0.416	0.463	0.472				
Hedon	0.790	0.762	0.788	0.460			
Intention	0.545	0.450	0.535	0.767	0.601		
Si	0.303	0.196	0.329	0.534	0.317	0.496	

Table 3 Fornell and Larcker's criterion

	Pe	Ee	Fc	Habit	Hedon	Intention	Si
Pe	**0.857**						
Ee	0.690	**0.914**					
Fc	0.643	0.794	**0.899**				
Habit	0.369	0.421	0.434	**0.889**			
Hedon	0.683	0.686	0.689	0.398	**0.934**		
Intention	0.478	0.409	0.481	0.667	0.517	**0.885**	
Si	0.269	0.186	0.306	0.474	0.282	0.444	**0.932**

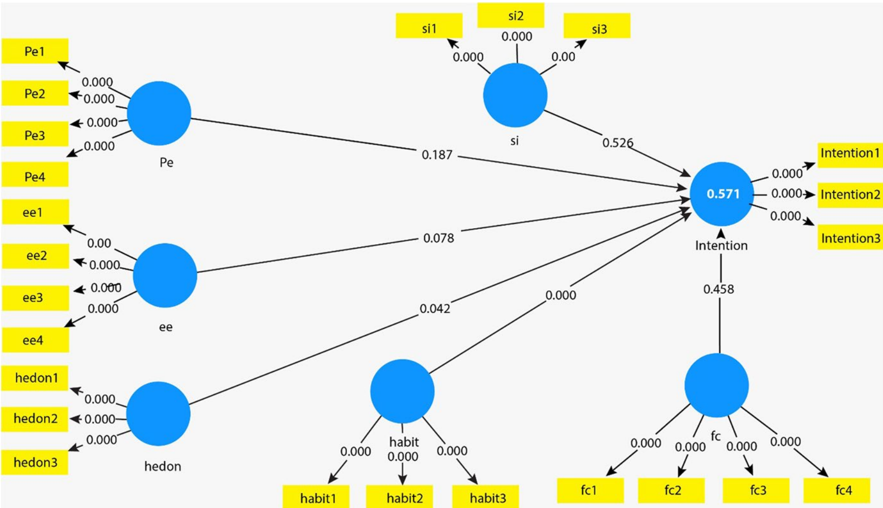

Fig. 3 Bootstrapped

researchers can estimate the path coefficient, which represents the strength and direction of the relationship between variables in a structural equation model. On the other hand, to determine the significance of a relationship, researchers often employ the bootstrap procedure, which allows them to obtain the corresponding p-value. In this regard, a common approach involves conducting the bootstrapping procedure with a substantial number of iterations, typically utilizing 5000 bootstrap samples (see Fig. 3).

Firstly, regarding performance expectancy, the beta value of 0.15 suggests a positive relationship, indicating that higher performance expectancy is associated with a greater intention to adopt AI in education. However, the p-value of 0.09 suggests that this relationship is not statistically significant. Consequently, the data does not provide sufficient evidence to support the hypothesis that performance expectancy influences the intention to adopt AI in education.

In contrast, the hypothesis regarding effort expectancy demonstrates a notable finding. The negative beta value of -0.24 indicates that as the perceived effort

Table 4 Cross loading

	Pe	ee	fc	habit	hedon	intention	si
Pe1	0.834	0.496	0.483	0.344	0.526	0.361	0.270
Pe2	0.919	0.646	0.564	0.373	0.632	0.462	0.162
Pe3	0.791	0.599	0.626	0.203	0.641	0.359	0.271
Pe4	0.878	0.614	0.540	0.332	0.550	0.443	0.239
Ee1	0.603	0.909	0.684	0.385	0.551	0.332	0.202
Ee2	0.662	0.934	0.787	0.416	0.645	0.388	0.199
Ee3	0.636	0.902	0.725	0.308	0.616	0.335	0.127
Ee4	0.619	0.911	0.705	0.417	0.681	0.424	0.153
Fc1	0.536	0.719	0.936	0.468	0.631	0.495	0.350
Fc2	0.646	0.779	0.913	0.413	0.668	0.453	0.229
Fc3	0.561	0.633	0.844	0.244	0.547	0.314	0.230
Habit1	0.309	0.377	0.337	0.902	0.325	0.526	0.515
Habit2	0.236	0.300	0.313	0.890	0.279	0.615	0.420
Habit3	0.434	0.444	0.497	0.874	0.449	0.625	0.341
Hedon1	0.674	0.655	0.656	0.349	0.939	0.501	0.224
Hedon2	0.600	0.626	0.630	0.395	0.929	0.463	0.306
Intention1	0.513	0.442	0.514	0.528	0.580	0.870	0.325
Intention2	0.361	0.303	0.329	0.635	0.330	0.880	0.432
Intention3	0.395	0.339	0.430	0.608	0.459	0.904	0.423
Si1	0.266	0.201	0.292	0.474	0.265	0.440	0.944
Si2	0.198	0.099	0.209	0.416	0.217	0.369	0.905
Si3	0.280	0.209	0.344	0.431	0.301	0.427	0.946

required to use AI decreases, the intention to adopt it increases. This negative relationship is statistically significant, as reflected by the p-value of 0.03. Hence, there is evidence to support the hypothesis that lower effort expectancy is linked to a higher intention to adopt AI in education.

Furthermore, the hedonistic aspect exhibits a positive and significant relationship with to adoption of AI. The beta value of 0.37 signifies that the pleasure derived from using AI in education leads to a higher intention to adopt it. This finding is supported by the statistically significant p-value of 0.02.

Likewise, the hypothesis regarding habit reveals a strong relationship. The positive beta value of 0.41 suggests that a higher habit of using AI in education is associated with a higher intention to adopt it among postgraduate students. This relationship is highly significant, indicated by the p-value of 0.00. Therefore, there is strong evidence to support the hypothesis that habit influences the intention to adopt AI in education.

In contrast, the hypotheses related to facilitating conditions and social influence do not yield statistically significant results. The beta values of 0.10 and 0.05, respectively, suggest positive relationships. However, the p-values of 0.22 and 0.26 indicate a lack of statistical significance, indicating that the data does not provide enough evidence to support the hypotheses. Thus, facilitating conditions and social

Table 5 Hypothesis testing

Hypothesis	Beta value	t-value	p-value	remarks	R^2	f^2	SRMR
Performance expectancy → intention	0.15	1.32	0.09	Not supported	0.57	0.02	0.069
Effort expectancy → intention	-0.24	1.76	0.03	Not supported		0.02	
Hedonistic → intention	0.37	2.03	0.02	supported		0.04	
Habit → intention	0.41	4.84	0.00	supported		0.35	
Facilitating condition → intention	0.10	0.74	0.22	Not supported		0.01	
Social influence → intention	0.05	0.63	0.26	Not supported		0.01	

p-values are denoted with asterisks (*)

*$p < 0.05$

**$p < 0.01$

***$p < 0.001$

influence may have a limited impact on the intention to adopt AI in education among postgraduate students in Malaysia, based on the given data.

Additionally, it is worth noting that the research model demonstrates a high level of model fit. The SRMR (Standardized Root Mean Square Residual) value, which measures the standardized root mean square residual, is below the threshold of 0.08 as proposed by (Hu & Bentler, 1998). Furthermore, the analysis reveals that the relationship between Performance expectancy and intention to adopt AI in education among postgraduate students in Malaysia demonstrates a small effect size of 0.02. Similarly, the relationship between Effort expectancy and intention also exhibits a small effect size of 0.02. Additionally, the association between Hedonistic factors and intention indicates a slightly larger effect size of 0.04. Notably, the relationship between Habit and intention reveals a substantial effect size of 0.35, suggesting a strong influence. Conversely, the relationships between Facilitating conditions and Social influence with intention exhibit minimal effect sizes of 0.01 each, indicating limited impact in this context.

3 Discussion

The primary objective of this study is to ascertain the key factors that contribute to the acceptance of artificial intelligence technology among postgraduate students in Malaysia. The growing prevalence of ICT technology highlights its role as an efficient medium for performing diverse tasks. Within this context, the adoption of artificial intelligence among students is also witnessing significant traction. Consequently, research focusing on the acceptance of artificial intelligence technology among students, particularly postgraduate students, holds paramount importance. The study findings provide empirical evidence supporting the influence of hedonistic values on the intention to use artificial intelligence technology among postgraduate students. This suggests that students who possess hedonistic values are more inclined to adopt and utilize artificial intelligence technology in their educational pursuits. The findings of this study align with the research conducted by Venkatesh et al., (2012a, 2012b), which also demonstrated a significant relationship between hedonic factors and the intention to use computer technology.

One noteworthy discovery in this study pertains to the absence of a significant relationship between performance expectancy and the intention to continue using AI. This finding aligns with previous research conducted by Utaminingsih et al. (2023) in the domain of sustainable business model innovation. The possible explanation for this finding could be attributed to the widespread utilization of AI technology among post-graduate students, leading them to develop entrenched usage patterns. These patterns can be characterized as habitual behaviours that are reinforced through repetitive engagement. Consequently, while initial expectations regarding AI performance may be lofty, the sustained use of AI is primarily driven by habituation rather than ongoing performance evaluation. In addition, our study identified habit as significant and to be the strongest predictor of postgraduate students' intention to use AI. This suggests that habit factors play a critical role in AI acceptance among this population. Our findings suggest that fostering habitual AI use in everyday life could be a key strategy to promote AI adoption among postgraduate students. This highlights the importance of interventions that encourage postgraduate students to integrate AI tools into their workflows and daily activities.

A noteworthy contribution to the field emerges from the observation that effort expectancy influences AI adoption. Extant research consistently demonstrates a positive relationship between effort expectancy and technology adoption. However, the present study suggests a potential divergence from this established pattern. This deviation might be attributed to the existence of efficacious, non-AI-driven solutions for the tasks undertaken by postgraduate students. If these traditional methods are perceived as simpler to utilize and yield comparable outcomes, students may exhibit a preference for them over the perceived intricacy of AI-powered solutions.

By omitting the price construct in line with the contextual relevance of artificial intelligence technology among postgraduates in Malaysia, this study makes a significant contribution to the advancement of the UTAUT 2 theory, thereby enhancing the construct within this specific domain.

In summary, the findings highlight that while performance expectancy, facilitating conditions, and social influence may not significantly influence the intention to adopt AI in education, factors such as effort expectancy, hedonistic experiences, and habit play important roles in shaping the adoption intention. These results provide valuable insights for policymakers and educational institutions aiming to enhance AI integration in the educational context for postgraduate students in Malaysia.

4 Conclusion

In conclusion, the utilization of artificial intelligence (AI) among students is experiencing global recognition, yet Malaysia still lacks comprehensive research and information in this domain. This quantitative study aimed to fill this gap by identifying the factors that contribute to the adoption of AI among postgraduate students. By focusing on the postgraduate student population in Malaysia and employing simple sampling techniques, this study successfully shed light on the underlying determinants of AI adoption. The findings of this research revealed that two variables, namely hedonistic and habit, play a significant role in influencing the adoption of AI among postgraduate students. This implies that the pleasure derived from using AI technologies and the habitual integration of AI into daily academic routines are key factors that drive its uptake among postgraduate students in Malaysia. These research findings hold valuable implications for various stakeholders involved in the future implementation of AI technologies among postgraduate students. By gaining a deeper understanding of the influential factors, relevant parties, such as educational institutions and policymakers, can devise effective strategies to enhance the utilization of AI in the postgraduate education landscape.

Overall, this study contributes to the existing literature on AI adoption among students, specifically focusing on the postgraduate level in Malaysia. It highlights the significance of hedonistic and habit factors in driving AI adoption. It is anticipated that these findings will assist stakeholders in making informed decisions and advancing the integration of AI technologies in postgraduate education, ultimately equipping students with the necessary skills and competencies for the evolving digital era.

Acknowledgements The authors like to extend our gratitude to Universiti Teknologi MARA Cawangan Pahang and Universiti Islam Pahang Sultan Ahmad Shah management for their academic support.

Authors' contributions The allocation of authorship responsibilities in this research is delineated as follows: Mohd Amli and Badli Esham undertook the composition of the introduction and literature review sections. Data collection was conducted jointly by Mohd Amli and Fahmi Zaidi. Fahmi Zaidi, Wan Hashridz Rizal, and Nur Aulia Fahada collectively contributed to the development of hypotheses, design of the research methodology, as well as the formulation of the discussion and conclusion sections.

Funding No funding was received or declared for the reported research.

Data availability All data generated or analysed during this study are included in this published article.

Declarations

Competing interests The authors declare that they have no competing interests.

References

Afrizal, D., & Wallang, M. (2021). Attitude on intention to use e-government in Indonesia. *Indonesian Journal of Electrical Engineering and Computer Science, 22*(1), 435–441.

Ahmad, N. M. F., Husin, N. N. A. A., Ahmad, N. A. N. A., Abdullah, N. H., Wei, N. C. S., & Nawi, N. M. N. M. (2022). Digital transformation: An exploring barriers and challenges practice of artificial intelligence in manufacturing firms in Malaysia. *Journal of Advanced Research in Applied Sciences and Engineering Technology, 29*(1), 110–117. https://doi.org/10.37934/araset.29.1.110117

Akgun, S., & Greenhow, C. (2021). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics, 2*(3), 431–440. https://doi.org/10.1007/s43681-021-00096-7

Alomari, A. S. A., & Abdullah, N. L. (2023). Factors influencing the behavioral intention to use Cryptocurrency among Saudi Arabian public university students: Moderating role of financial literacy. *Cogent Business & Management, 10*(1), 2178092.

Asatryan, S., & Matevosyan, A. (2023). Revolutionary changes in higher education with artificial intelligence. *Main Issues of Pedagogy and Psychology, 10*(1), 76–86. https://doi.org/10.24234/miopap.v10i1.454

Ashraf, R. U., Hou, F., & Ahmad, W. (2019). Understanding continuance intention to use social media in China: The roles of personality drivers, hedonic value, and utilitarian value. *International Journal of Human-Computer Interaction, 35*(13), 1216–1228.

Ayensa, E. J., Mosquera, A. M., & Murillo, Y. S. (2016). Omnichannel customer behavior: key drivers of technology acceptance and use and their effects on purchase intention. *Frontiers in Psychology, 7*. https://doi.org/10.3389/fpsyg.2016.01117

Azizi, S. M., Roozbahani, N., & Khatony, A. (2020). *Factors affecting the acceptance of blended learning in medical education: application of utaut2 model*. https://doi.org/10.21203/rs.3.rs-27351/v1

Bengio, Y., Courville, A., & Vincent, P. (2021). Representation learning: A review and new perspectives. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 43*(4), 652–664.

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management, 57*(2), 103168.

Biliavska, V., Castanho, R. A., & Vulevic, A. (2022). Analysis of the impact of artificial intelligence in enhancing human resource practices. *Journal of Intelligent Management Decision, 1*(2), 128–136. https://doi.org/10.56578/jimd010206

Bozkurt, A., Karadeniz, A., Baneres, D., Guerrero-Roldán, A., & Rodríguez, M. E. (2021). Artificial intelligence and reflections from educational landscape: A review of AI studies in half a century. *Sustainability, 13*(2), 800. https://doi.org/10.3390/su13020800

Chai, S. Y., Hayat, A., & Flaherty, G. (2022). Integrating artificial intelligence into haematology training and practice: Opportunities, threats and proposed solutions. *British Journal of Haematology, 198*(5), 807–811. https://doi.org/10.1111/bjh.18343

Chan, K. M. A., & Zary, N. (2019). Applications and challenges of implementing artificial intelligence in medical education: Integrative review. *JMIR Medical Education, 5*(1), e13930. https://doi.org/10.2196/13930

Chan, R., Troshani, I., Rao Hill, S., & Hoffmann, A. (2022). Towards an understanding of consumers' FinTech adoption: The case of Open Banking. *International Journal of Bank Marketing, 40*(4), 886–917.

Chauke, T. A., Mkhize, T. R., Methi, L., & Dlamini, N. (2024). Postgraduate students' perceptions on the benefits associated with artificial intelligence tools on academic success: in case of chatgpt ai tool. *Journal Of Curriculum Studies Research, 6*(1), 44–59. https://doi.org/10.46303/jcsr.2024.4

Chen, K.-W., Hsu, Y.-C., & Shiue, Y.-M. (2023). Examination of students' intention to continue using problem-based learning in a healthcare information course in terms of self-efficacy, social influence, and motivation. *AIP Conference Proceedings*, 2685(1). AIP Publishing.

Cokins, G., Oncioiu, I., Türkeș, M. C., Topor, D. I., Căpuşneanu, S., Paștiu, C. A., Deliu, D., & Solovăstru, A. N. (2020). Intention to use accounting platforms in Romania: A quantitative study on sustainability and social influence. *Sustainability, 12*(15), 6127.

Dakduk, S., Santalla-Banderali, Z., & Woude, D. V. D. (2018). Acceptance of blended learning in executive education. *SAGE Open, 8*(3), 215824401880064. https://doi.org/10.1177/2158244018800647

Foroughi, B., Iranmanesh, M., Kuppusamy, M., Ganesan, Y., Ghobakhloo, M., & Senali, M. G. (2023). Determinants of continuance intention to use gamification applications for task management: An extension of technology continuance theory. *The Electronic Library, 41*(2/3), 286–307.

Gharaibeh, M. K., Gharaibeh, N. K., Khan, M. A., Abu-ain, W. A. K., & Alqudah, M. K. (2021). Intention to use mobile augmented reality in the tourism sector. *Computer Systems Science and Engineering, 37*(2), 187–202.

Goli, M., & Khan, M. (2022). Behavioural intention to use social networking mobile apps: The case of TikTok. *International Journal of Business Innovation and Research, 29*(1), 16–31.

Hair, J. F., Jr., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research, 109*, 101–110.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. *Journal of Marketing Theory and Practice*. https://doi.org/10.2753/mtp1069-6679190202

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2014). A Primer on Partial Least Squares StructuralEquation Modeling (PLS-SEM). *Sage*, Thousand Oaks. https://doi.org/10.1108/EBR-10-2013-0128

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature.

Hu, L. T., & Bentler, P. M. (1998). Fit Indices in Covariance Structure Modeling: Sensitivity to Underparameterized Model Misspecification. *Psychological Methods*. https://doi.org/10.1037/1082-989X.3.4.424

Huang, Y.-M. (2020). What drives students to continue using social mindtools? The perspectives of social support and social influence. *Computers in Human Behavior, 111*, 106447.

Huang, J., Saleh, S., & Liu, Y. (2021). A review on artificial intelligence in education. *Academic Journal of Interdisciplinary Studies, 10*(3), 206. https://doi.org/10.36941/ajis-2021-0077

Huang, D., Shufang, X., & Xu, G. (2016).Construction of quality monitoring system in postgraduate education. *Proceedings of the 2016 2nd International Conference on Social Science and Higher Education*. https://doi.org/10.2991/icsshe-16.2016.28

Huangfu, H. (2023). Comparing the quality assurance system of postgraduate education in china and the united kingdom. *BCP Business and Management, 41*, 191–195. https://doi.org/10.54691/bcpbm.v41i.4429

Khalid, B., Lis, M., Chaiyasoonthorn, W., & Chaveesuk, S. (2021). Factors influencing behavioural intention to use MOOCs. *Engineering Management in Production and Services, 13*(2), 83–95.

Khayer, A., Talukder, M. S., Bao, Y., & Hossain, M. N. (2023). Application-based mobile payment systems: Continuance intention and intention to recommend. *International Journal of Mobile Communications, 21*(1), 19–53.

Koul, S., & Eydgahi, A. (2020). The impact of social influence, technophobia, and perceived safety on autonomous vehicle technology adoption. *Periodica Polytechnica Transportation Engineering, 48*(2), 133–142.

Kwon, H. (2023). Implementing artificial intelligence education for middle school technology education in the Republic of Korea. *International Journal of Technology and Design Education*. https://doi.org/10.1007/s10798-023-09812-2

Lainjo, B., & Tsmouche, H. (2023). Impact of artificial intelligence on higher learning institutions. *International Journal of Education, Teaching, and Social Sciences, 3*(2), 96–113. https://doi.org/10.47747/ijets.v3i2.1028

Leander, K. M., & Burriss, S. K. (2020). Critical literacy for a posthuman world: When people read, and become, with machines. *British Journal of Educational Technology, 51*(4), 1262–1276. https://doi.org/10.1111/bjet.12924

Lee, J., Wu, A. S., Li, D., & Kulasegaram, K. (2021). Artificial intelligence in undergraduate medical education: A scoping review. *Academic Medicine, 96*(11S), S62–S70. https://doi.org/10.1097/acm.0000000000004291

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly, 31*, 705–737.

Liu, S., Reese, T. S., Kawamoto, K., Fiol, G. D., & Weir, C. R. (2021). A systematic review of theoretical constructs in CDS literature. *BMC Medical Informatics and Decision Making, 21*(1). https://doi.org/10.1186/s12911-021-01465-2

Lucena, F. J. H., Díaz, I. A., Reche, M. P. C., & Rodríguez, J. M. R. (2019). Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature. *Education Sciences, 9*(1), 51. https://doi.org/10.3390/educsci9010051

Luo, X., Qin, M. S., Fang, Z., & Qu, Z. (2020). Artificial intelligence coaches for sales agents: Caveats and solutions. *Journal of Marketing, 85*(2), 14–32. https://doi.org/10.1177/0022242920956676

McCarthy, J. (2007). *What is artificial intelligence*. Retrieved from https://www-formal.stanford.edu/jmc/whatisai/whatisai.html. Accessed 7 Sept 2023

Murdick, D. A., Dunham, J., & Melot, J. (2020). *Ai definitions affect policymaking*. https://doi.org/10.51593/20200004

Musikanski, L., Rakova, B., Phillips, R., & Manson, M. (2020). Artificial intelligence and community well-being: A proposal for an emerging area of research. *International Journal of Community Well-Being, 3*(1), 39–55. https://doi.org/10.1007/s42413-019-00054-6

Nazari, N., Shabbir, M. S., & Setiawan, R. (2021). Application of artificial intelligence powered digital writing assistant in higher education: Randomized controlled trial. *Heliyon, 7*(5), e07014. https://doi.org/10.1016/j.heliyon.2021.e07014

Okunlaya, R. A., Abdullah, N. S., & Alias, R. A. (2022). Artificial intelligence (ai) library services innovative conceptual framework for the digital transformation of university education. *Library Hi Tech, 40*(6), 1869–1892. https://doi.org/10.1108/lht-07-2021-0242

Omorogiuwa, O., Ohiagu, K., & Lawal, K. H. (2023). Towards the review of artificial intelligence programme curriculum and effective collaborations among academia for ai programme development in africa. *Advances in Multidisciplinary and Scientific Research Journal Publication, 9*(1), 1–14. https://doi.org/10.22624/aims/digital/v11n1p1

Ou, Y. and Si, W. (2014). Several reflections on postgraduate innovation and entrepreneurship education. *Advances in Economics, Business and Management Research*. https://doi.org/10.2991/msmi-14.2014.10

Pane, J. F., Griffin, B. A., McCaffrey, D. F., & Karam, R. (2014). Effectiveness of cognitive tutor algebra I at scale. *Educational Evaluation and Policy Analysis, 36*(2), 127–144.

Popovič, A., & Sábo, J. (2021). Taxation of robots and AI – problem of definition. *Financial Law Review, 25*(1), 1–16. https://doi.org/10.4467/22996834flr.22.001.15651

Puspitaningsih, S., Irhadtanto, B., & Puspananda, D. R. (2022). The role of artificial intelligence in children's education for a digital future. *KnE Social Sciences*. https://doi.org/10.18502/kss.v7i19.12483

Rahi, S., Mansour, M. M. O., Alghizzawi, M., & Alnaser, F. M. (2019). Integration of UTAUT model in Internet banking adoption context: The mediating role of performance expectancy and effort expectancy. *Journal of Research in Interactive Marketing, 13*(3), 411–435.

Seo, K. W. (2020). A study on the application of kiosk service as the workplace flexibility: The determinants of expanded technology adoption and trust of quick service restaurant customers. *Sustainability, 12*(21), 8790. https://doi.org/10.3390/su12218790

Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner–instructor interaction in online learning. *International Journal of Educational Technology in Higher Education, 18*(1). https://doi.org/10.1186/s41239-021-00292-9

Tenakwah, E. S., Boadu, G., Tenakwah, E. J., Parzakonis, M., Brady, M., Kansiime, P., … & Berman, A. (2023). *Generative AI and higher education assessments: a competency-based analysis*. https://doi.org/10.21203/rs.3.rs-2968456/v1

Tominc, P., & Rožman, M. (2023). Artificial intelligence and business studies: Study cycle differences regarding the perceptions of the key future competences. *Education Sciences, 13*(6), 580. https://doi.org/10.3390/educsci13060580

Utaminingsih, A., Widowati, S. Y., & Witjaksono, E. H. (2023). Sustainable business model innovation: external and internal factors on SMEs. *International Journal of Innovation Science, 16*(1).

Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: a synthesis and the road ahead. *Journal of the Association for Information Systems, 17*(5), 328–376. https://doi.org/10.17705/1jais.00428

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a unified view. *MIS Quarterly*. https://doi.org/10.1017/CBO9781107415324.004

Venkatesh, V., Thong, J. Y.,& Xu, X. (2012a). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology by Viswanath Venkatesh, James Y.L. Thong, Xin Xu :: SSRN. *MIS Quarterly, 36*(1), 157-178.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012b). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly: Management Information Systems*. https://doi.org/10.2307/41410412

Walle, A. D., Jemere, A. T., Tilahun, B., Endehabtu, B. F., Wubante, S. M., Melaku, M. S., Tegegne, M. D., & Gashu, K. D. (2023). Intention to use wearable health devices and its predictors among diabetes mellitus patients in Amhara region referral hospitals, Ethiopia: Using modified UTAUT-2 model. *Informatics in Medicine Unlocked, 36*, 101157.

Wang, Y.-Y., Wang, Y.-S., & Jian, S.-E. (2020). Investigating the determinants of students' intention to use business simulation games. *Journal of Educational Computing Research, 58*(2), 433–458.

Watanabe, A. (2023). *Studierende im ki-diskurs. Künstliche Intelligenz in Der Hochschulbildung*, 99–118. https://doi.org/10.14361/9783839457696-006

Wood, E., Ange, B., & Miller, D. (2021). Are we ready to integrate artificial intelligence literacy into medical school curriculum: Students and faculty survey. *Journal of Medical Education and Curricular Development, 8*, 238212052110240. https://doi.org/10.1177/23821205211024078

Wu, Y. (2024). Study on the impact of utilizing chatgpt and other ai tools for feedback in eap writing classrooms on the discursive writing performance of english major students. *Transactions on Social Science, Education and Humanities Research, 4*, 143–150. https://doi.org/10.62051/4se95x52

Yang, D., Oh, E., & Wang, Y. (2020). Hybrid physical education teaching and curriculum design based on a voice interactive artificial intelligence educational robot. *Sustainability, 12*(19), 8000. https://doi.org/10.3390/su12198000

Yang, F., Ren, L., & Gu, C. (2022). A study of college students' intention to use metaverse technology for basketball learning based on UTAUT2. *Heliyon, 8*(9), e10562.

Yawised, K., Apasrawirote, D., Chatrangsan, M., & Muneesawang, P. (2022). Factors affecting SMEs' intention to adopt a mobile travel application based on the unified theory of acceptance and use of technology (UTAUT-2). *Emerging Science Journal, 4*, 207–224. https://doi.org/10.28991/esj-2021-sp1-014

Yu, L. and Yu, Z. (2023). Qualitative and quantitative analyses of artificial intelligence ethics in education using Vosviewer and Citnetexplorer. *Frontiers in Psychology, 14*. https://doi.org/10.3389/fpsyg.2023.1061778

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

Zhou, T. (2022). Examining online health community users' sharing behaviour: A social influence perspective. *Information Development, 38*(4), 599–608.

Zhou, M., Huang, J., Wu, K., Huang, X., Kong, N., & Campy, K. S. (2021). Characterizing Chinese consumers' intention to use live e-commerce shopping. *Technology in Society, 67*, 101767.