Research Article https://doi.org/10.12973/eu-jer.13.1.183

European Journal of Educational Research
Volume 13, Issue 1, 183 - 195.
ISSN: 2165-8714
http://www.eu-jer.com/

New Challenges of Learning Accounting With Artificial Intelligence: The Role of Innovation and Trust in Technology

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Received: March 29, 2023 ▪ Revised: May 22, 2023 ▪ Accepted: June, 5, 2023

Abstract: Online learning has become increasingly popular, making the learning process more attractive. One of the most popular learning media is artificial intelligence (AI). However, students do not accept this technology at all. Therefore, this study examined the factors influencing accounting students' acceptance of AI in learning. The survey was conducted with 147 higher-education students who use AI as a learning medium. The data were analyzed using SmartPLS 4.0 with the partial least square approach. The results showed that perceived usefulness influenced behavioral intention to use and satisfaction. However, perceived ease of use was only significant for satisfaction. Similarly, perceived confidence must be consistent with intention. Although it may influence perceived usefulness, other constructs, such as AI quality and personal innovativeness, can increase students' perceptions of the benefits and convenience of adopting AI in learning. Thus, this study contributes to the development of the technology acceptance model (TAM) and the information systems success model and is helpful to scholars, especially in applying AI in learning. They need to pay attention to the quality of AI, such as the accuracy of the information produced. Thus, the need to control the information from the AI only serves as a reference without requiring you to trust it completely.

Keywords: *Artificial intelligence, online learning, perceived trust, personal innovativeness, technology adoption.*

To cite this article: Musyaffi, A. M., Baxtishodovich, B. S., Afriadi, B., Hafeez, M., Adha, M. A., & Wibowo, S. N. (2024). New challenges of learning accounting with artificial intelligence: The role of innovation and trust in technology. *European Journal of Educational Research, 13*(1), 183-195. https://doi.org/10.12973/eu-jer.13.1.183

Introduction

Since COVID-19, online learning-based learning models have been developed rapidly. Even after COVID-19, online learning methods are still used because they can be flexibly organized for the learning process. Online learning can enable students and lecturers to carry out learning activities anywhere and anytime, making it easier for both parties (Musyaffi, Septiawan et al., 2022). Combining technology with online learning impacts educational goals in higher education, such as reducing costs, increasing student learning, and effective management (Alkhawaja et al., 2022; Hadullo et al., 2017).

Online learning can also increase intense communication between students and lecturers. However, more than online learning is needed to increase student engagement in the studied subjects. A fun and effortless approach to learning is necessary to improve the efficiency of online learning. One possible solution is integrating artificial intelligence (AI) technology. AI allows the learning process to be carried out interactively and quickly in producing information. The field of education has even led to extensive applications such as AI (Chassignol et al., 2018; Miyaji, 2019; Zawacki-Richter et al., 2019). AI utilizes massive analytical data processing to mimic human-like functions that have been scientifically researched to improve online learning and blended learning (Ouyang et al., 2023). One of these functions is increasing learning efficiency and developing instructional designs for the learning process (Nabizadeh et al., 2020; Ouyang et al., 2023; Taheri et al., 2021). Therefore, using technology in learning is required (López-Belmonte et al., 2020).

The existence of AI shows the progress of high technological developments because of its ability to improve human capabilities at a low cost. However, in professional or cultural contexts, AI cannot mimic or replace the need for human

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contact, regardless of its use. To validate the best theoretical models for predicting the adoption of AI technology, further research should be conducted using the naturalistic technique. Such a study is necessary to comprehend the aspects contributing to AI user acceptability, such as perceived benefits, ease of use, attitudes, trust, and satisfaction from AI users (Kelly et al., 2023).

Research conducted by BestColleges proves that 70% of students indicated that online learning is better than learning in class, and even 95% of graduates recommend online learning to others (BestColleges, 2022). This finding proves that online learning is an effective method of the learning process. However, a report from SMR revealed that when 92% of students studied online, they faced issues such as insufficient guidance from teachers and poor internet connectivity, with 38% affected by these problems (Hemansyah, 2020). Online learning systems have the possibility of losing, so there is a need for support from teachers, curricula, monitoring, and evaluation, as well as remedial systems (Munoz-Najar et al., 2022). Although online learning has many benefits for lecturers, students, and institutions in the learning process, research has indicated that only 15% of online learning initiatives are successful. In comparison, 40% partially fail, and the remaining 45% result in complete failure (Almaiah et al., 2020).

Practitioners and academics must evaluate the AI tools used in accounting education, as students may have varying acceptance levels towards them. One crucial way to increase user acceptance is to evaluate the technology acceptance model (TAM) (Martín-García et al., 2019; Venkatesh & Bala, 2008). TAM can determine student acceptance of technology by analyzing the frequency of use and gauging their perceptions of how convenient and beneficial technology is in their learning experience. The TAM model is widely used to evaluate technology acceptance, particularly in education. It focuses on the benefits and convenience provided by the system. Students tend to accept technologies that have user-friendly menus that are easy to see and use during the learning process (Martín-García et al., 2019; Muti Altalhi, 2021). Even though AI functions can be used anywhere and provide accurate results, their use by students is increasing. In the IS success model, user satisfaction can be measured by the system's quality contained in the technology. The quality of the used technology tends to make users feel accessible and helpful when utilizing the system, so the impact on user satisfaction is growing. This research examines the acceptance and successful implementation of online learning with AI. To achieve this aim, this study integrates TAM and IS success models and extends them to include factors such as trust and innovativeness. These factors are identified as research problems that require further investigation.

Literature Review

Artificial Intelligence Quality (AIQ)

The system's quality can be shown from the functionality of the system according to user needs and has minimal risk (DeLone & McLean, 2003). Previous literature has shown that the high quality of technology students use increases the perception that instructional media benefits learning (Musyaffi, Septiawan, et al., 2022; Sulaiman et al., 2023). System quality is also critical in increasing usefulness (Alkhawaja et al., 2022; Mahmoodi et al., 2017) and student satisfaction (Al-Fraihat et al., 2020). Therefore, improving the system's quality is crucial, especially regarding user convenience and benefits that foster student satisfaction. In addition, proper feedback through online learning can increase student satisfaction (Al-Adwan et al., 2021). Feature of quality technology is that it comes from the functionality of an online learning system that can be quickly learned (Balaman & Baş, 2021; Musyaffi, Sulistyowati, et al., 2022). This is so that when the system's quality is high, it will directly affect student perceptions that learning with the help of technology can provide reliable and valuable functionality for increasing learning satisfaction (Al-Adwan et al., 2021). It is worth noting that when a system has all the features and benefits needed, students' perceived benefits and convenience for this technology are getting bigger and can be used continuously. This argument is fully supported by several previous studies when the quality of the system is good, and the user tends to have a perception of usability (Al-Adwan et al., 2021; Alkhawaja et al., 2022; Mohamed Riyath & Muhammed Rijah, 2022; Sulaiman et al., 2023) and convenience (Stylios et al., 2022; Sulaiman et al., 2023), which becomes greater. Based on this explanation, hypotheses 1, 2, and 3 are as follows:

H1: Artificial Intelligence Quality (AIQ) has a positive impact on perceived usefulness (PUAI)

H2: Artificial Intelligence Quality (AIQ) has a positive impact on Perceived Ease of Use (PEAI)

H3: Artificial Intelligence Quality (AIQ) has a positive impact on Student Satisfaction (SSA)

Perceived Usefulness (PUAI)

In TAM theory, usefulness is an essential element impacting technology adoption. Even in the digital learning system domain, PUAI has been proven to be a factor that triggers the acceptance of technology used in education (Rugube & Govender, 2022). PUAI is a person's beliefs about technologies that can improve performance and efficiency, especially in daily activities (Davis, 1989). PUAI is defined as the level of student confidence in using AI, which can assist students in improving the learning process to be more effective and efficient. As technology function increases, students are more satisfied using it in every lesson (Duggal, 2022; Musyaffi, Septiawan, et al., 2022). This opinion has been supported by previous literature, which confirms that PUAI can increase user satisfaction and help the learning process (Jain et al., 2022). In addition, a good perception of benefits regarding the technology used can increase user adoption (Alami & El

Idrissi, 2022; Hu et al., 2022; Martín-García et al., 2019; Musyaffi, Sulistyowati, et al., 2022; Sulaiman et al., 2023). Thus, the 4th and 5th hypotheses are as follows:

H4: Perceived Usefulness (PUAI) has a positive impact on Behavior Intention (BIA)

H5: Perceived Usefulness (PUAI) has a positive impact on Student Satisfaction (SSA)

Perceived Ease of Use (PEAI)

Ease of use indicates how positively students perceive technology that does not take substantial effort to learn (Musyaffi, Sulistyowati, et al., 2022). Ease of use in learning with AI refers to the ability to master AI with less effort. The easier the tools students use, the greater the benefits and uses (Dissanayake & Velananda, 2020; Stylios et al., 2022; Suki & Suki, 2017). So that it allows students to use technology in every learning process (Abdullah et al., 2016; Maheshwari, 2021). The majority of previous research regarding the adoption of online learning implemented with the TAM model revealed a strong relationship between convenience and usability (Chen & Li, 2021; Maheshwari, 2021; Mailizar et al., 2021; Mohamed Riyath & Muhammed Rijah, 2022; Munabi et al., 2020).

H7: Perceived Ease of Use (PEAI) has a positive impact on Perceived Usefulness (PUAI)

H8: Perceived Ease of Use (PEAI) has a positive impact on Student Satisfaction (SSA)

Perceived Trust (PTA)

Trust is viewed as existing when an institution or party has faith in the dependability and honesty of a partner (Morgan & Hunt, 1994). Trust in the educational context is understood in students' beliefs in a system or institution used in the educational process. Trust is also essential to influence student attitudes toward using technology in learning (Hameed et al., 2022). Trust in the technology used is critical to make users continue to use the product. The results of previous research prove a strong interest between trust, usefulness, and intention (Ahmed & Damodharan, 2022; Kaur et al., 2022; Rafferty & Fajar, 2022). Unsurprisingly, trust is the most crucial issue in technology adoption (Boo & Chua, 2022; Chiu et al., 2017; Stylios et al., 2022). Hence, the 9th and 10th hypotheses in this study are as follows:

H9: Perceived Trust (PTA) has a positive impact on Behavior Intention (BIA)

H10: Perceived Trust (PTA) has a positive impact on Perceived Usefulness (PUAI)

Personal Innovativeness (PIA)

PIA is individual readiness and desire to experiment with new information technology, unaffected by external or internal factors (Agarwal & Prasad, 1998). In learning with AI, PIA is defined as the readiness of students to try online learning technology using AI based on their characteristics. Students with a high level of innovation tend to perceive technology as a new use that can facilitate their learning process (Čevra et al., 2022). It can be concluded that PIA has a significant impact on PUAI (Cheng & Huang, 2013; Liébana-Cabanillas et al., 2015). The higher the level of user innovation, the greater the perception of benefit to students, leading to continued use of the technology (Liébana-Cabanillas et al., 2015; Rahman, 2013). In addition, the current literature has also proven a positive and significant relationship between PIA and the user's intention (Ahmed & Damodharan, 2022; Suebtimrat & Vonguai, 2021). Therefore, hypotheses 11 and 12 in this study are:

H11: Personal Innovativeness (PIA) has a positive impact on Perceived Usefulness (PUAI)

H12: Personal Innovativeness (PIA) has a positive impact on Perceived Ease of Use (PEAI)

Student Satisfaction (SSA)

Satisfaction is a significant factor in the successful model framework for implementing certain technologies (DeLone & McLean, 2003; Forster et al., 2020). Student satisfaction in this study indicates that students are satisfied with using technology because it is convenient and provides benefits that help students improve their understanding. For example, in mobile learning, the tendency of students to use mobile learning is greater if they are more satisfied (Izkair & Lakulu, 2021). That is, when students have felt satisfaction when using online learning with AI, students will likely continue to use AI in online learning. Previous research also ascertains a strong relationship between satisfaction and intention (Kaur et al., 2022; Musyaffi, Septiawan, et al., 2022; Rejman Petrović et al., 2022). The 13th hypothesis in this study is as follows:

H13: Student Satisfaction (SSA) positively impacts Behavior Intention (BIA).

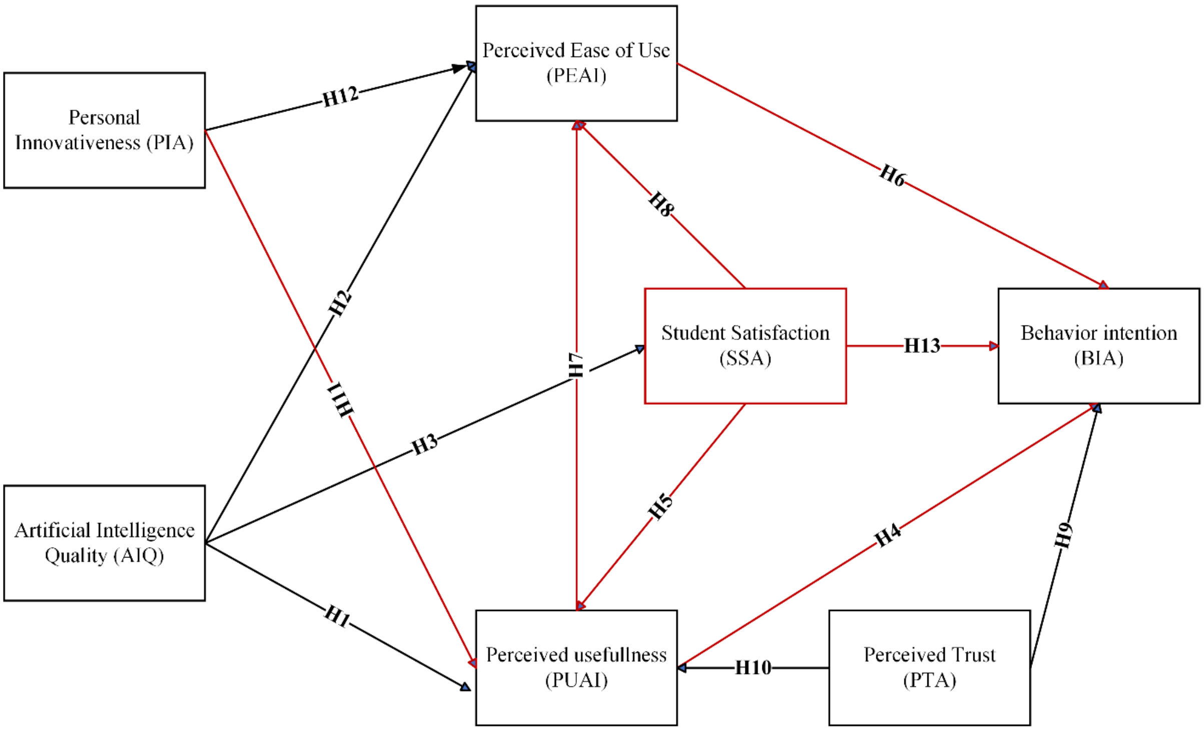

Figure 1. Research Model

Methodology

Research Design

This study used quantitative methods to answer research problems. With the help of a questionnaire, the data was processed and interpreted to explain the facts that occurred in the field. Questionnaires were distributed online to management information systems and accounting information systems students after they used AI to complete accounting-related tasks. The AI used was chatbot, grammar, and paraphrasing. The researcher used a census technique to obtain the number of samples, namely, taking all samples into the population. The reason was that the population in this study was all students in the Management Information Systems (3 classes) and Accounting Information Systems (3 classes) courses with 161 students. All incoming data were pre-screened using the frequency and statistical distribution available in the SmartPLS 4 feature. After that, the author ensured that the data was complete. If the data were incomplete, the author rechecked the completeness of the data. However, after the first check, it was found that 14 respondents had answered incompletely and did not respond. Hence, the total number of participants was 147 respondents, resulting in a response rate of 91.9%. The response rate's magnitude can continue in quantitative research (Babbie, 2020).

Instrument

Each question in this study was adapted from previous researchers for the research problem. The questionnaire that was distributed was closed-ended. A total of 27 questions were distributed to the students. Each question consisted of 5 responses, ranging from "strongly disagree" (scored 1) to "strongly agree" (scored 4). Each construct item was taken from different previous studies according to the research problem. The AIQ construct consisted of 4 questions (Ojo, 2017). Moreover, the PTA construct consisted of 3 questions (Hameed et al., 2022). While the PUAI and PEAI are part of TAM, each consisted of 4 questions adopted from Venkatesh and Bala (2008). The SSA construct was adopted from Kim et al., (2007), consisting of 4 questions. Finally, BIA items were adopted from several previous researchers (Hameed et al., 2022).

Data Analysis

The researcher used SEM-PLS analysis with SmartPLS 4 software to answer the hypotheses. Researchers used the PLS method because it could predict the built model (Hair & Alamer, 2022). This was so that researchers can understand how far the constructs that have been built form a model. The stages in SEM PLS consisted of two primary analyses: evaluating the measurement model by looking at validity (outer loading and AVE) and construct reliability (CR and CA). After that, testing with HTMT and Fornell-Larcker was carried out to ensure that no collinearity occurred. In the second stage, the authors evaluated the output of SmartPLS 4.0 on structural modeling through the coefficient of determination (R^2) and predictive relevance (Q^2) taken from blindfolding data. In the last stage, the researcher evaluated the hypothesis proposed with SmartPLS output 4.

Findings/Results

Measurement Model

The first stage was to evaluate the outer loading (minimum .7) and AVE (minimum .5). After that, reliability was evaluated through CR and CA with a minimum value of 0.7 (Hair & Alamer, 2022).

Table 1. Measurement Model Output

Item	Outer loading	VIF	CA	AVE	CR
Artificial Intelligence Quality (AIQ)			.852	.693	.900
AIQ1	.857	2.552			
AIQ2	.777	1.542			
AIQ3	.852	2.576			
AIQ4	.841	1.962			
Perceived Trust (PTA)			.877	.802	.924
PTA1	.873	2.274			
PTA2	.914	2.912			
PTA3	.900	2.304			
Personal Innovativeness (PIA)			.872	.726	.913
PIA1	.841	2.187			
PIA2	.910	3.510			
PIA3	.893	2.855			
PIA4	.756	1.578			
Perceived Ease of Use (PEAI)			.911	.790	.938
PEAI1	.880	2.683			
PEAI2	.903	3.071			
PEAI3	.893	2.877			
PEAI4	.879	2.607			
Perceived Usefulness (PUAI)			.913	.793	.939
PUAI1	.909	4.143			
PUAI2	.916	4.274			
PUAI3	.862	2.333			
PUAI4	.874	2.598			
Student Satisfaction (SSA)			.868	.717	.910
SSA1	.879	2.522			
SSA2	.865	2.372			
SSA3	.787	1.726			
SSA4	.854	2.101			
Behavior Intention (BIA)			.869	.719	.911
BIA1	.896	2.891			
BIA2	.830	1.981			
BIA3	.845	2.312			
BIA4	.819	1.937			

Outer loading values in this study ranged from .756 – .916. In contrast, the AVE value is 0.693 – 0.802. All items contained good data validity because they had a value above .7 (the smallest value is .756). In comparison, the reliability aspect was measured based on CA (CA values = .852 – .916) and CR (CR values = .900 – .939). Then on the reliability aspect, the research data is reliable because it met the CR and CA criteria above .7.

Furthermore, to ensure that no collinearity occurs, VIF evaluation was used. The recommended VIF value does not exceed 5 (Hair & Alamer, 2022). Based on Table 1 above, the VIF values for all items do not exceed 5 (1.542 – 4.274), so it can be concluded that the items in this study have no collinearity.

The purpose of the HTMT evaluation was to ensure that no correlation occurred in any research items. The way to evaluate HTMT was to look at the items produced by HTMT with a value below .9 one by one (Hair & Alamer, 2022). In total, the details of the HTMT output from SmartPLS 4 are presented as follows:

Table 2. Discriminant Validity With HTMT

	AIQ	BIA	PUAI	PEAI	PTA	PIA
BIA	.615					
PUAI	.643	.721				
PEAI	.691	.726	.744			
PTA	.779	.543	.409	.576		
PIA	.458	.589	.513	.605	.556	
SSA	.664	.843	.696	.779	.651	.716

The HTMT value on the BIA – AIQ item is .615. In contrast, PUAI with AIQ (.643) and BIA (.721) has a value below .9. Likewise, PEAI with AIQ (.691), BIA (.691), and PUAI (.409). While other constructs, such as PTA, PIA, and SSA, have HTMT values below .9. Based on the presentation of the HTMT evaluation, all items met the discriminant validity criteria in the HTMT aspect.

After evaluating the value of the HTMT, the next step was to test the discriminant validity using the Fornell-Larker, which must have a root value of AVE above other values. For example, AIQ items with AIQ have a value of .833, where the value was greater than the AIQ construct with BIA (.532), PUAI (.572), PEAI (.614), PTA (.680), PIA (.398), SSA (.578). Then BIA items with BIA also have a value of .848. At the same time, BIA with other constructs such as PUAI (.645), PEAI (.647), PTA (.478), PIA (.516), and SSA (.733) has a smaller value than BIA with BIA. Then the PEAI – PEAI construct (.889) has the most significant value compared to PEAI with PTA (.519), PIA (.545), and SSA (.692). The PTA and PTA constructs (.896) also have the highest HTMT values when compared to other constructs, such as PTA and PIA (.487) and SSA (.570). While the PIA construct with PIA has a more excellent value than PIA with SSA. Based on this evaluation, all have the most outstanding value to meet the discriminant validation criteria using Fornell-Larcker.

Table 3. Discriminant Validity With Fornell-Larcker

	AIQ	BIA	PUAI	PEAI	PTA	PIA	SSA
AIQ	.833						
BIA	.532	.848					
PUAI	.572	.645	.890				
PEAI	.614	.647	.679	.889			
PTA	.680	.478	.369	.519	.896		
PIA	.398	.516	.458	.545	.487	.852	
SSA	.578	.733	.623	.692	.570	.627	.847

Structural Model

To test the model's suitability, analyze the R square and predictive relevance (Q^2). The results of R^2 and Q^2 based on the output of SmartPLS 4 are as follows:

Table 4. R square and Q2

	R^2	Q^2
BIA	.607	.360
PUAI	.523	.368
PEAI	.485	.467
Student Satisfaction (SSA)	.543	.443

R^2 was used to predict the ability of the dependent variable model, which can be predicted using the independent variable. The R^2 value for BIA is .607, which means that the model built by BIA has a moderate explanatory power of 60.7%. At the same time, R^2 for PUAI has a moderate explanatory score of 52.3%. While the R^2 values for PEAI and SSA were respectively 48.5% and 54.3% in the category of moderate explanatory power.

While the Q^2 value indicates the appropriateness of the model the researcher has built when the value is more than 0, Q^2 is obtained based on the SmartPLS 4.0 output in the calculation of the blindfolding method. The table above shows the Q^2 value with the smallest to the most extensive range, .360 – .467. Q^2 value for BIA is .360; there is a 36% fit between PEAI, PTA, PUAI, and SSA with BIA. Then the Q^2 value for the PUAI construct of .368 indicates an appropriate model level of 36.8% in the AIQ, PTA, and PEAI constructs of PUAI. Then in the SSA construct, the model's reasonable rate is 44.3%. In contrast, the PEAI construct has the highest Q^2 value compared to BIA, SSA, and PUAI, .467. The model built against PEAI, namely AIQ, and PIA, has a high model fit rate of 46.7%.

Hypotheses Testing

The hypothesis testing phase was conducted to evaluate the results of SmartPLS, the proposed hypotheses, and the determined error rate. Each hypothesis is classified as significant in Table 5 below.

Table 5. Hypotheses Testing

Hypotheses		Path	p values	Support
H1	AIQ -> PUAI	.342	.001	Yes
H2	AIQ -> PEAI	.472	.000	Yes
H3	AIQ -> SSA	.188	.015	Yes
H4	PUAI -> BIA	.252	.003	Yes
H5	PUAI -> SSA	.230	.013	Yes
H6	PEAI -> BIA	.135	.063	No
H7	PEAI -> PUAI	.485	.000	Yes
H8	PEAI -> SSA	.421	.000	Yes
H9	PTA -> BIA	.059	.212	No
H10	PTA -> PUAI	.187	.021	Yes
H11	PIA -> PUAI	.148	.010	Yes
H12	PIA -> PEAI	.357	.000	Yes
H13	SSA -> BIA	.449	.000	Yes

The first to third hypotheses regarding AIQ for PUAI, PEAI, and SSA have *p* values of .001, .000, and .015, respectively. All three are above 0.05, so the AIQ construct for PUAI, PEAI, and SSA has a hypothesis accepted with a magnitude of influence of 34.2% (AIQ □ PUAI), 47.2%, and 18.8%. Then H4 (PUAI □ BIA) and H5 (PUAI □ SSA) have *p* values of .003 and .013, so hypotheses 4 and 5 are also accepted with a relationship level of 25.2% and 23%. This result shows that PUAI is one of the constructs that strengthens the TAM theory. From the aspect of PEAI, it can also strengthen TAM, but only for PUAI. PEAI on SSA also has a strong impact, with a magnitude of influence of 42.1%. Unfortunately, PEAI to BIA in this study did not have a vital significance ($p = .063$, $p > .05$). Likewise, students' perceptions of belief in AI learning in the 9th hypothesis results do not significantly impact the adoption of AI in online learning ($p = .212$).

Discussion

This study used the integration between TAM and the IS success model and additional variables such as personal innovativeness and perceived trust to determine the acceptability and success of implementing AI in online learning. The analysis with PLS showed that all technology acceptance variables could be well predicted with TAM, except for PEAI, which was shown to have no significant relationship with the adoption of AI in online learning. This result is because students are more interested in AI functions that help them ask questions or solve accounting problems quickly. Previous researchers also confirmed the findings of this study that PEAI does not significantly impact the intention to use (Cheng & Huang, 2013; Rafferty & Fajar, 2022; Yan et al., 2021).

However, behind the rejection of the significance of PEAI, another variable in TAM, namely PUAI, has a positive impact on the adoption of AI in online learning ($p < .000$), which means that the ease of use of AI in online learning can strengthen its benefits and usability. Therefore, students who feel that the AI used in learning is easy to use will more easily experience the benefits of learning using AI. The convenience most widely felt is the menu and how to use it, which is easy and fast. In addition, students also benefit a lot from the information output generated by AI, especially in helping solve problems related to economic events. Students tend to prioritize the use of AI in learning. This research's findings are similar to those of other researchers, revealing a relationship between convenience and usefulness (Sulaiman et al., 2023; Thi et al., 2023) and usefulness with technology adoption, especially in learning (Efiloğlu Kurt, 2022; Musyaffi, Septiawan, et al., 2022; Sinha & Bag, 2023; Sulaiman et al., 2023; Wang et al., 2022).

The use of technology provides many conveniences for students, one of which is being able to understand the material better with the help of AI. For example, students can quickly improve their writing grammar for making assignments. In addition, students can also paraphrase writing. When encountering unfamiliar terms, students can ask AI chatbots to discover student problems, especially those related to accounting. Students may also ask for journaling and financial reports. Although not 100% true, students believe that AI is a reference for developing ideas and solving problems in the learning process. This finding follows previous research where the trust gained through technology increases the intensity of technology use (Arfi et al., 2021). One inhibiting factor is the risks inherent in this technology which causes users to feel doubtful (Musyaffi, Gurendrawati, et al., 2022). The higher the features and benefits of the technology used for learning, the higher the student acceptance. This result is because students' use of technology, particularly AI, is primarily for learning purposes in everyday life; thus, AI can facilitate student comprehension in accounting learning.

This research also proves that PIA affects PEAI and PUAI by 14.8% and 35.7%, respectively. The results indicate that students' preparedness significantly impacts how they perceive the convenience and advantages of AI, particularly its features and benefits. This fact is because students currently have high digital literacy. Students are already familiar with the technology, so it is easier to master the technology itself. In addition, COVID-19 has also increased the use of technology in general, as other subjects require the use of technology in online learning. It stands to reason that students with a high level of technology readiness will accept and use technology in learning because the wealth of information available makes it easy for them (Čevra et al., 2022; Stylios et al., 2022). This research finding is also confirmed by other research, which confirms that the higher the PIA, the more users can experience the benefits of higher technology (Cheng & Huang, 2013; Jain et al., 2022; Liébana-Cabanillas et al., 2015; Shanmugavel & Micheal, 2022).

Trust occurs when students are satisfied with the features and benefits of AI, which increases the adoption of continuous learning in a positive way (Hameed et al., 2022). When students see that others have extensively used AI-related content, it becomes more familiar to them and enhances their perception of the usefulness of AI. Besides that, trust is an essential key factor in forming successful collaboration in applying technology (Chiu et al., 2017; Suki & Suki, 2017). The study results confirmed the researcher's opinion that PTA had a significant impact on student BIAI, which was found to be 18.7%. This result shows that the level of usefulness of students in using AI depends on their trust in the information contained in the AI. Other studies reveal that AI applied to the learning process can increase learning efficiency and develop more attractive instructional designs (Nabizadeh et al., 2020; Ouyang et al., 2023; Taheri et al., 2021).

The quality of AI affects student behavior during the learning process. This fact is evident from the use of AI, which refers to the quality of AI, especially accuracy, flexibility, and ease of features and services. That statement is under what Field DeLone and McLean (2003) revealed that a quality system would improve the performance and function of the system itself. System quality is one of the critical factors for successful system implementation, especially in online learning for students (Hadullo et al., 2017; Musyaffi, Sulistyowati et al., 2022). Students believe using AI in learning accounting is very beneficial, especially when dealing with unfamiliar terms and problem-solving. This result leads to high satisfaction with using AI in online learning. These results were also confirmed by previous studies where there was a substantial factor between system quality and convenience, and usability (Alkhawaja et al., 2022; Mohamed Riyath & Muhammed Rijah, 2022; Sulaiman et al., 2023) as well as with student satisfaction (Almaiah & Alismaiel, 2019; Lutfi et al., 2022). The higher the quality of AI students use, the higher the possibility for students to find it easy and valuable, resulting in students feeling more satisfied. If the quality of the system is related to the degree to which students perceive the benefits of this technology resulting from online learning, this quality will lead to a decision by students to use online learning regularly (Alkhawaja et al., 2022; Musyaffi et al., 2021).

If students cannot develop a positive attitude in utilizing their skills, they will tend not to master them even though the tools are very effective (Ajzen, 1991; Fredrickson, 2001). The same is true with AI learning. Even though AI can help students improve learning understanding, if it is responded to negatively, it will affect student studies' success (Suh & Ahn, 2022). The results of this study indicate a high level of satisfaction with AI, so students will continue to use AI for learning in other subjects.

In addition, the model in this study proves that 44.5% can confirm the variance for student satisfaction and 36% for behavioral intention. The results show that students perceive using AI in online learning to be more convenient and appropriate and to help students learn. This finding leads to BI being high in the learning process. These results also follow previous researchers who found a high level of BI (Mailizar et al., 2021; Mohamed Riyath & Muhammed Rijah, 2022).

Conclusion

The results of this study show an increase in the TAM model integrated with the IS model of success in using AI for online learning. All variables in TAM, such as PUAI, can increase student intention. However, PEAI could not positively increase the importance of students' use of AI in online learning. One factor influencing this result is that students are more interested in the features that can help students in the learning process, mainly because of the speed in solving student problems. In addition, the variables in TAM, namely PEUI and PUAI, also increase students' satisfaction so that they continuously use AI as a learning medium in every lesson. The quality of AI greatly affects how easily and user-friendly students perceive it. Therefore, it is essential to significantly improve the features and menus of AI to help students solve their problems correctly. This result also aligns with the construct of trust, which can improve student perception. Students receive recommendations from others in internal and external environments, such as social media, so they believe AI can improve learning. Students can accept the use of AI in online learning if others are also satisfied with the use of AI. One of the factors is the quality of the functions and menus that help students in the learning process.

Recommendations

The role of technology in education is crucial, especially when considering the acceptance of the latest advancements, such as AI, among accounting students. Therefore, researching this topic is essential. This study can help develop a technology adoption theory to measure AI in online learning. The results also show that AI quality, confidence, and personal innovativeness are essential in developing technology acceptance models. Thus, when implementing learning with AI, it is important to consider these factors in addition to the constructs of technology acceptance theory. In addition, the results of this study can serve as a recommendation for lecturers to integrate technological approaches such as AI into the learning process. However, lecturers must also set clear boundaries for the use of AI so that students do not adopt the entire output of AI. After all, in essence, technology like AI only helps people achieve their goals. In addition, this research's results also inspire academics to create superior technology-based learning models by providing the right ecosystem through personal innovation. This ecosystem is built through routine learning with technology so that students are comfortable with adapting learning to all types of technology. The researchers also recommend other variables that may influence the adoption of AI in online learning, such as technology readiness, self-efficacy, and instructor quality. In addition, the researchers suggest adding an endogenous variable, such as student performance.

Limitations

This research is limited to using the TAM and IS success models and two variables: personal innovativeness and perceived trust. Future research should examine the use of AI in education using other theoretical approaches, such as social cognitive theory or mental accounting theory, to provide a new perspective on student acceptance of learning with AI. In addition, only accounting students participated in this study. Therefore, results may differ for students in other disciplines. This study can be useful for scholars researching how AI is used in various fields and academic programs.

Authorship Contribution Statement

Musyaffi: Drafting manuscript, statistical analysis, conceptualization, data analysis, final approve. Baxtishodovich: Drafting manuscript, data acquisition, concept and design. Afriadi: Data distribution, drafting manuscript, concept and design. Hafeez: Concept and design, drafting manuscript, statistical analysis. Adha: Drafting manuscript, analysis data. Wibowo: Writing, data analysis, data acquisition.

References

Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of e-portfolios. *Computers in Human Behavior*, *63*, 75–90. https://doi.org/10.1016/j.chb.2016.05.014

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, *9*(2), 101–215. https://doi.org/10.1287/isre.9.2.204

Ahmed, K. A. A., & Damodharan, V. S. (2022). Antecedents of QR code acceptance during Covid-19: Towards sustainability. *Transnational Marketing Journal*, *10*(1), 171–199.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Al-Adwan, A. S., Albelbisi, N. A., Hujran, O., Al-Rahmi, W. M., & Alkhalifah, A. (2021). Developing a holistic success model for sustainable E-Learning: A structural equation modeling approach. *Sustainability*, *13*(16), Article 9453. https://doi.org/10.3390/su13169453

Alami, Y., & El Idrissi, I. (2022). Students' adoption of e-learning: Evidence from a Moroccan business school in the COVID-19 era. *Arab Gulf Journal of Scientific Research*, *40*(1), 54–78. https://doi.org/10.1108/AGJSR-05-2022-0052

Al-Fraihat, D., Joy, M., Masa'deh, R., & Sinclair, J. (2020). Evaluating E-learning systems success: An empirical study. *Computers in Human Behavior*, *102*, 67–86. https://doi.org/10.1016/j.chb.2019.08.004

Alkhawaja, M. I., Halim, M. S. A., Abumandil, M. S. S., & Al-Adwan, A. S. (2022). System quality and student's acceptance of the E-learning system: The serial mediation of perceived usefulness and intention to use. *Contemporary Educational Technology*, *14*(2), Article ep350. https://doi.org/10.30935/cedtech/11525

Almaiah, M. A., & Alismaiel, O. A. (2019). Examination of factors influencing the use of mobile learning system: An empirical study. *Education and Information Technologies*, *24*, 885–909. https://doi.org/10.1007/s10639-018-9810-7

Almaiah, M. A., Al-Khasawneh, A., & Althunibat, A. (2020). Exploring the critical challenges and factors influencing the E-learning system usage during COVID-19 pandemic. *Education and Information Technologies*, *25*, 5261–5280. https://doi.org/10.1007/s10639-020-10219-y

Arfi, W. B., Nasr, I. B., Kondrateva, G., & Hikkerova, L. (2021). The role of trust in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context. *Technological Forecasting and Social Change*, *167*, Article 120688. https://doi.org/10.1016/j.techfore.2021.120688

Babbie, E. R. (2020). *The practice of social research* (15th ed.). Cengage Learning.

Balaman, F., & Baş, M. (2021). Perception of using e-learning platforms in the scope of the technology acceptance model (TAM): A scale development study. *Interactive Learning Environments.* Advance online publication. https://doi.org/10.1080/10494820.2021.2007136

BestColleges. (2022). *Online education trends report*. https://bit.ly/3PonYoL

Boo, H. C., & Chua, B.-L. (2022). An integrative model of facial recognition check-in technology adoption intention: The perspective of hotel guests in Singapore. *International Journal of Contemporary Hospitality Management*, *34*(11), 4052–4079. https://doi.org/10.1108/IJCHM-12-2021-1471

Čevra, B., Kapo, A., Zaimović, T., & Turulja, L. (2022). E-Learning in organizations: Factors affecting individual job performances. *International Journal of Emerging Technologies in Learning*, *17*(2), 189-208. https://doi.org/10.3991/ijet.v17i02.26967

Chassignol, M., Khoroshavin, A., Klimova, A., & Bilyatdinova, A. (2018). Artificial Intelligence trends in education: A narrative overview. *Procedia Computer Science*, *136*, 16–24. https://doi.org/10.1016/j.procs.2018.08.233

Chen, C., & Li, X. (2021). Understanding entity shared product usage: An innovation-adoption coupling model. *Asia Pacific Journal of Marketing and Logistics*, *34*(8), 1659–1680. https://doi.org/10.1108/APJML-04-2021-0279

Cheng, Y.-H., & Huang, T.-Y. (2013). High speed rail passengers' mobile ticketing adoption. *Transportation Research Part C: Emerging Technologies*, *30*, 143–160. https://doi.org/10.1016/j.trc.2013.02.001

Chiu, J. L., Bool, N. C., & Chiu, C. L. (2017). Challenges and factors influencing initial trust and behavioral intention to use mobile banking services in the Philippines. *Asia Pacific Journal of Innovation and Entrepreneurship*, *11*(2), 246–278. https://doi.org/10.1108/APJIE-08-2017-029

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

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

Dissanayake, D. M. R., & Velananda, Y. L. (2020). Critical success factors for performance-oriented M-Learning in Sri Lanka. *Journal of Educational and Social Research*, *10*(2), 112–125. https://doi.org/10.36941/jesr-2020-0031

Duggal, S. (2022). Factors impacting acceptance of e-learning in India: Learners' perspective. *Asian Association of Open Universities Journal*, *17*(2), 101–119. https://doi.org/10.1108/AAOUJ-01-2022-0010

Efiloğlu Kurt, Ö. (2022). Learning with smartphones: The acceptance of m-learning in higher education. *Online Information Review, 47*(5), 862-879. https://doi.org/10.1108/OIR-10-2021-0516

Forster, Y., Hergeth, S., Naujoks, F., Krems, J. F., & Keinath, A. (2020). What and how to tell beforehand: The effect of user education on understanding, interaction and satisfaction with driving automation. *Transportation Research Part F: Traffic Psychology and Behaviour*, *68*, 316–335. https://doi.org/10.1016/j.trf.2019.11.017

Fredrickson, B. L. (2001). The role of positive emotions in positive psychology. *The American Psychologist*, *56*(3), 218–226. https://doi.org/10.1037/0003-066X.56.3.218

Hadullo, K., Oboko, R., & Omwenga, E. (2017). A model for evaluating e-learning systems quality in higher education in developing countries. *International Journal of Education and Development Using ICT*, *13*(2), 185-204. https://www.learntechlib.org/p/180643/

Hair, J., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), Article 100027. https://doi.org/10.1016/j.rmal.2022.100027

Hameed, F., Qayyum, A., & Khan, F. A. (2022). A new trend of learning and teaching: Behavioral intention towards mobile learning. *Journal of Computers in Education*. Advance online publication. https://doi.org/10.1007/s40692-022-00252-w

Hemansyah, F. (2020, December 29). *Majority of students want to return to school in January: KPAI survey*. The Jakarta Post. https://bit.ly/thejakartapost2020

Hu, X., Zhang, J., He, S., Zhu, R., Shen, S., & Liu, B. (2022). E-learning intention of students with anxiety: Evidence from the first wave of COVID-19 pandemic in China. *Journal of Affective Disorders*, *309*, 115–122. https://doi.org/10.1016/j.jad.2022.04.121

Izkair, A. S., & Lakulu, M. M. (2021). Experience moderator effect on the variables that influence intention to use mobile learning. *Bulletin of Electrical Engineering and Informatics*, *10*(5), 2875–2883. https://doi.org/10.11591/eei.v10i5.3109

Jain, N. K., Kaul, D., & Sanyal, P. (2022). What drives customers towards mobile shopping? An integrative technology continuance theory perspective. *Asia Pacific Journal of Marketing and Logistics*, *34*(5), 922–943. https://doi.org/10.1108/APJML-02-2021-0133

Kaur, S., Katoch, R., & Rana, A. (2022). Exploring post-adoption behavior of the UPI users with cognitive and affective factors. *International Journal on Recent and Innovation Trends in Computing and Communication*, *10*(12), 140-154. https://doi.org/10.17762/ijritcc.v10i12.5895

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, *77*, Article 101925. https://doi.org/10.1016/j.tele.2022.101925

Kim, C., Jahng, J., & Lee, J. (2007). An empirical investigation into the utilization-based information technology success model: Integrating task–performance and social influence perspective. *Journal of Information Technology*, *22*(2), 152–160. https://doi.org/10.1057/palgrave.jit.2000072

Liébana-Cabanillas, F., Ramos de Luna, I., & Montoro-Ríos, F. J. (2015). User behaviour in QR mobile payment system: The QR Payment Acceptance Model. *Technology Analysis and Strategic Management*, *27*(9), 1031–1049. https://doi.org/10.1080/09537325.2015.1047757

López-Belmonte, J., Parra-González, M. E., Segura-Robles, A., & Pozo-Sánchez, S. (2020). Scientific mapping of gamification in Web of Science. *European Journal of Investigation in Health, Psychology and Education*, *10*(3), 832-847. https://doi.org/10.3390/ejihpe10030060

Lutfi, A., Saad, M., Almaiah, M. A., Alsaad, A., Al-Khasawneh, A., Alrawad, M., Alsyouf, A., & Al-Khasawneh, A. L. (2022). Actual use of mobile learning technologies during social distancing circumstances: case study of King Faisal University students. *Sustainability*, *14*(12), Article 7323. https://doi.org/10.3390/su14127323

Maheshwari, G. (2021). Factors affecting students' intentions to undertake online learning: An empirical study in Vietnam. *Education and Information Technologies*, *26*, 6629–6649. https://doi.org/10.1007/s10639-021-10465-8

Mahmoodi, Z., Esmaelzadeh-Saeieh, S., Lotfi, R., Baradaran Eftekhari, M., Akbari-Kamrani, M., Mehdizadeh-Tourzani, Z., & Salehi, K. (2017). The evaluation of a virtual education system based on the DeLone and McLean model: A path analysis. *F1000Research*, *6*, Article 1631. https://doi.org/10.12688/f1000research.12278.2

Mailizar, M., Burg, D., & Maulina, S. (2021). Examining university students' behavioural intention to use e-learning during the COVID-19 pandemic: An extended TAM model. *Education and Information Technologies*, *26*, 7057–7077. https://doi.org/10.1007/s10639-021-10557-5

Martín-García, A. V., Martínez-Abad, F., & Reyes-González, D. (2019). TAM and stages of adoption of blended learning in higher education by application of data mining techniques. *British Journal of Educational Technology*, *50*(5), 2484–2500. https://doi.org/10.1111/bjet.12831

Miyaji, I. (2019). Comparison of technical terms and consciousness of blended classes in 'AI technology' and 'artificial intelligence'. *European Journal of Educational Research, 8*(1), 107-121. https://doi.org/10.12973/eu-jer.8.1.107

Mohamed Riyath, M. I., & Muhammed Rijah, U. L. (2022). Adoption of a learning management system among educators of advanced technological institutes in Sri Lanka. *Asian Association of Open Universities Journal*, *17*(2), 161–177. https://doi.org/10.1108/AAOUJ-03-2022-0032

Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing*, *58*(3), 20–38. https://doi.org/10.2307/1252308

Munabi, S. K., Agusti, J., & Nabushawo, H. M. (2020). Using the TAM model to predict undergraduate distance learners behavioural intention to use the Makerere University learning management system. *Open Access Library Journal*, *7*, Article e6699. https://doi.org/10.4236/oalib.1106699

Munoz-Najar, A., Gilberto Sanzana, A. G., Hasan, A., Cobo Romani, J. C., Azevedo, J. P. W. D., & Akmal, M. (2022). *Remote learning during covid-19:* Lessons from today, principles for tomorrow. World Bank. https://bit.ly/43rXMgP

Musyaffi, A. M., Gurendrawati, E., Afriadi, B., Oli, M. C., Widawati, Y., & Oktavia, R. (2022). Resistance of traditional SMEs in using digital payments: Development of innovation resistance theory. *Human Behavior and Emerging Technologies*, *2022*, Article 7538042. https://doi.org/10.1155/2022/7538042

Musyaffi, A. M., Rosnidah, I., & Muna, A. (2021). Cloud-based learning management: An effective learning during social distancing. *Journal of Educational and Social Research*, *11*(5), 173–181. https://doi.org/10.36941/JESR-2021-0115

Musyaffi, A. M., Septiawan, B., Arief, S., Usman, O., Sasmi, A. A., & Zairin, G. M. (2022). What drives students to feel the impact of online learning in using a cloud accounting integrated system? *TEM Journal*, *11*(4), 1577–1588. https://doi.org/10.18421/TEM114-19

Musyaffi, A. M., Sulistyowati, W. A., Wolor, C. W., & Sasmi, A. A. (2022). Game-based learning sustainability during social distance: The role of gamification quality. *European Journal of Educational Research*, *11*(3), 1289–1302. https://doi.org/10.12973/EU-JER.11.3.1289

Muti Altalhi, M. (2021). Towards understanding the students' acceptance of MOOCs: A unified theory of acceptance and use of technology (UTAUT). *International Journal of Emerging Technologies in Learning*, *16*(2), 237–253. https://doi.org/10.3991/ijet.v16i02.13639

Nabizadeh, A. H., Leal, J. P., Rafsanjani, H. N., & Shah, R. R. (2020). Learning path personalization and recommendation methods: A survey of the state-of-the-art. *Expert Systems with Applications*, *159*, Article 113596. https://doi.org/10.1016/j.eswa.2020.113596

Ojo, A. I. (2017). Validation of the Delone and Mclean information systems success model. *Healthcare Informatics Research*, *23*(1), 60–66. https://doi.org/10.4258/hir.2017.23.1.60

Ouyang, F., Wu, M., Zheng, L., Zhang, L., & Jiao, P. (2023). Integration of artificial intelligence performance prediction and learning analytics to improve student learning in online engineering course. *International Journal of Educational Technology in Higher Education*, *20*, Article 4. https://doi.org/10.1186/s41239-022-00372-4

Rafferty, N. E., & Fajar, A. N. (2022). Integrated QR payment system (QRIS): Cashless payment solution in developing country from merchant perspective. *Asia Pacific Journal of Information Systems*, *32*(3), 630–655. https://doi.org/10.14329/apjis.2022.32.3.630

Rahman, M. M. (2013). Barriers to M-commerce adoption in developing countries – a qualitative study among the stakeholders of Bangladesh. *The International Technology Management Review*, *3*(2), 80–91. https://doi.org/10.2991/itmr.2013.3.2.2

Rejman Petrović, D., Nedeljković, I., & Marinković, V. (2022). The role of the hedonistic and utilitarian quality dimensions in enhancing user satisfaction in mobile banking. *International Journal of Bank Marketing*, *40*(7), 1610–1631. https://doi.org/10.1108/IJBM-03-2022-0112

Rugube, T. T., & Govender, D. (2022). Evaluation of a software model for integrating learning management systems and massive open online courses. *International Journal of Innovative Research and Scientific Studies*, *5*(3), 170-183. https://doi.org/10.53894/ijirss.v5i3.493

Shanmugavel, N., & Micheal, M. (2022). Exploring the marketing related stimuli and personal innovativeness on the purchase intention of electric vehicles through Technology Acceptance Model. *Cleaner Logistics and Supply Chain*, *3*, Article 100029. https://doi.org/10.1016/j.clscn.2022.100029

Sinha, A., & Bag, S. (2023). Intention of postgraduate students towards the online education system: Application of extended technology acceptance model. *Journal of Applied Research in Higher Education*, *15*(2), 369–391. https://doi.org/10.1108/JARHE-06-2021-0233

Stylios, I., Kokolakis, S., Thanou, O., & Chatzis, S. (2022). Key factors driving the adoption of behavioral biometrics and continuous authentication technology: An empirical research. *Information & Computer Security*, *30*(4), 562–582. https://doi.org/10.1108/ICS-08-2021-0124

Suebtimrat, P., & Vonguai, R. (2021). An investigation of behavioral intention towards QR code payment in Bangkok, Thailand. *The Journal of Asian Finance, Economics and Business*, *8*(1), 939–950. https://doi.org/10.13106/jafeb.2021.vol8.no1.939

Suh, W., & Ahn, S. (2022). Development and validation of a scale measuring student attitudes toward artificial intelligence. *SAGE Open*, *12*(2), 1-12. https://doi.org/10.1177/21582440221100463

Suki, N. M., & Suki, N. M. (2017). Flight ticket booking app on mobile devices: Examining the determinants of individual intention to use. *Journal of Air Transport Management*, *62*, 146–154. https://doi.org/10.1016/j.jairtraman.2017.04.003

Sulaiman, T. T., Mahomed, A. S. B., Rahman, A. A., & Hassan, M. (2023). Understanding antecedents of learning management system usage among university lecturers using an integrated TAM-TOE model. *Sustainability*, *15*(3), Article 1885. https://doi.org/10.3390/su15031885

Taheri, A., RahimiZadeh, K., & Rao, R. V. (2021). An efficient balanced teaching-learning-based optimization algorithm with individual restarting strategy for solving global optimization problems. *Information Sciences*, *576*, 68–104. https://doi.org/10.1016/j.ins.2021.06.064

Thi, H. P., Tran, Q. N., La, L. G., Doan, H. M., & Vu, T. D. (2023). Factors motivating students' intention to accept online learning in emerging countries: The case study of Vietnam. *Journal of Applied Research in Higher Education*, *15*(2), 324–341. https://doi.org/10.1108/JARHE-05-2021-0191

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

Wang, K., van Hemmen, S. F., & Criado, J. R. (2022). The behavioural intention to use MOOCs by undergraduate students: Incorporating TAM with TPB. *International Journal of Educational Management*, *36*(7), 1321–1342. https://doi.org/10.1108/IJEM-11-2021-0446

Yan, L.-Y., Tan, G. W.-H., Loh, X.-M., Hew, J.-J., & Ooi, K.-B. (2021). QR code and mobile payment: The disruptive forces in retail. *Journal of Retailing and Consumer Services*, *58*, Article 102300. https://doi.org/10.1016/j.jretconser.2020.102300

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*, Article 39. https://doi.org/10.1186/s41239-019-0171-0