Pak. j. life soc. Sci. (2024), 22(2):16725-16741 E-ISSN: 2221-7630;P-ISSN: 1727-4915

Pakistan Journal of Life and Social Sciences

www.pjlss.edu.pk

https://doi.org/10.57239/PJLSS-2024-22.2.001215

RESEARCH ARTICLE

The Mediating Role of Artificial Intelligence Readiness on Accounting Students' Learning Performance: An Exploration of Communicativeness, Interactivity, Mobility and Autonomy Moderated by Technology Readiness

Mengrong Han[1], Hasri Mustafa Abdul Razak[2*], Saira Kharuddin[3]

[1,2,3] School Of Business and Economics, Universiti Putra Malaysia, 43400 Serdang, Selangor, MALAYSIA

ARTICLE INFO

Received: Sep 17, 2024

Accepted: Nov 29, 2024

Keywords

Artificial Intelligence Readiness

Technology Readiness

Accounting Education

Learning Performance

Communicative

Interactive

Mobility

Autonomy

Structural Equation Modelling

Multilevel Analysis

***Corresponding Author:**

hasyie@upm.edu.my

ABSTRACT

Focusing on the transformative impact of Artificial Intelligence (AI) and technology in accounting education, this study examines how AI readiness, as a mediating variable, and technology readiness, as a moderating variable, affect the learning performance of accounting students. The study used structural equation modelling (SEM) and multilevel analysis to construct a comprehensive theoretical framework with communicative, interactive, mobile and autonomous as the core constructs. Through a large-scale questionnaire survey (N=1000) of accounting students in several universities across China, this study revealed the mediating mechanism of AI readiness between educational technology characteristics and learning outcomes, as well as the moderating effect of technology readiness. The findings indicated that AI readiness significantly enhanced the positive effects of communicativeness, interactivity, mobility, and autonomy on learning performance, while technology readiness strengthened this mediating effect. This study not only enriches the theoretical knowledge in the field of accounting education, but also provides empirical evidence for colleges and universities to formulate AI-integrated education strategies and enhance students' digital literacy, which is of great significance in promoting the modernisation of accounting education and cultivating high-quality accounting talents adapted to the smart era.

1. INTRODUCTION

1.1 Background and significance of the study

In today's digital age, artificial intelligence (AI) and information technology are profoundly changing industries, and the accounting field is no exception. With the rapid development of technologies such as big data, cloud computing and machine learning, traditional accounting practice and education models are facing unprecedented challenges and opportunities (Quattrone, 2016).The global outbreak of the New Crown Epidemic in 2020 has accelerated the digital transformation of the education sector, with distance learning and online education becoming the new normal (Liang et al., 2022). In this context, exploring how AI and technology affect the learning process and learning outcomes of accounting students has become a common focus of attention in both academia and practice.

Accounting education, as a key link in training future accounting talents, has a direct bearing on the long-term development of the accounting industry in terms of its quality. The traditional accounting education model has been difficult to meet the demand for composite accounting talents in the intelligent era. Therefore, integrating AI and advanced technology into accounting education can not only improve teaching efficiency and learning effect, but also cultivate students' digital literacy and innovation ability, laying a solid foundation for their future career development (Pincus et al., 2017).

However, the introduction of technology does not necessarily lead to improved learning outcomes. Students' AI Readiness and Technology Readiness largely determine whether they can effectively utilise these new tools and platforms (Parasuraman & Colby, 2015). Therefore, an in-depth study of the role of AI readiness and technology readiness in accounting education is of great theoretical and practical significance for optimising instructional design, improving learning outcomes, and cultivating high-quality accounting talents adapted to the smart era.

1.2 Research questions and objectives

Against the above background, this study aims to explore the following core issues:

How do the core characteristics of educational technology (communicative, interactive, mobile, autonomous) affect the learning performance of accounting students?

Does AI readiness play a mediating role between educational technology characteristics and learning performance? If so, what are the mechanisms of action?

How does technology readiness moderate the mediating effect of AI readiness?

In order to answer these questions, the following specific objectives were set for this study:

Towards a comprehensive theoretical framework integrating communicativeness, interactivity, mobility and autonomy to systematically analyse the impact of educational technology features on learning performance.

To validate the role of AI readiness as a mediating variable and reveal its transmission mechanism between educational technology adoption and learning outcomes.

Explore the role of technology readiness as a moderating variable and analyse how it affects the strength of the mediating effect of AI readiness.

Based on the findings, empirical evidence and policy recommendations are provided for accounting education reform, AI integration strategy development and students' digital literacy development.

1.3 Theoretical contribution and practical value

This study has significant value at both the theoretical and practical levels. At the theoretical level, firstly, this study extends the application of the Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI) theory in accounting education. By introducing the new variable of AI readiness, it further enriches the existing theoretical framework and provides a more complete perspective to explain the application of technology in accounting education. In addition, this study systematically explores the mediating role of AI readiness in the application of accounting education technology for the first time, which fills the gaps in existing research and lays the foundation for future related studies. By examining the moderating effect of technology readiness, this study deepens the understanding of the complex mechanisms of technology application in education and reveals how technology readiness affects the effectiveness of AI technology in education. Finally, this study integrates the four dimensions of communicativeness, interactivity, mobility, and autonomy to propose a more comprehensive framework for assessing the characteristics of educational technology, which not only enriches the theoretical research in related fields, but also provides an effective tool for subsequent empirical studies.

At the practical level, this study provides an empirical basis for colleges and universities to formulate AI-integrated education strategies, which can effectively optimise the teaching design and resource allocation, and thus enhance the quality of teaching. At the same time, this study provides specific directions for improving the AI readiness and technology readiness of accounting students, which is crucial for cultivating high-quality accounting talents adapted to the smart era. In addition, this study provides accounting educators with new perspectives for evaluating and improving the effectiveness of teaching and learning, helping them to continuously improve their teaching methods from the perspective of technology integration and promoting the continuous improvement of education quality. Finally, this study provides an important reference for the talent cultivation policy of the accounting industry, especially in the context of the increasing contradiction between the digital transformation of the industry and the supply of talent, the results of the study can provide effective decision-making support for policy makers, thus promoting the sustainable development of the accounting industry.

2. LITERATURE REVIEW

2.1 Current status of research on the use of technology in accounting education

In recent years, with the rapid development of digital technology, the application of technology in accounting education has been increasingly researched.Apostolou et al.'s (2019) review of accounting education research in 2018 shows that the application of technology in accounting programmes has become a major research theme. This trend reflects a general academic interest in adapting accounting talent development for the digital age. Early studies focused on the effectiveness of computer-assisted instruction and the application of online learning platforms, such as Holtzblatt and Tschakert (2011) who explored the use of digital video technology in accounting education. As technology advances, the focus of research has gradually shifted to more advanced technological tools such as big data analytics, artificial intelligence and blockchain.

A study by Sledgianowski et al. (2017) suggests that incorporating big data analytics skills into accounting curricula is critical to enhancing students' employability. This view has been recognised by the accounting professional accreditation bodies, with the American Institute of Certified Public Accountants (AICPA) having included data analytics skills in the CPA exam syllabus. Meanwhile, the use of AI technology in accounting education has also attracted much attention.Kokina and Davenport (2017) explore how AI is changing the practice of auditing and emphasise the importance of fostering AI literacy among students in accounting education. These studies not only focus on the technology itself, but also explore how it is changing the knowledge structure and skill requirements of the accounting profession.

The importance of technology applications in accounting education is generally recognised, but empirical research on the specific mechanisms of their impact is still limited. In particular, there is still a significant lack of existing research on how AI readiness and technology readiness affect learning outcomes. In addition, most of the studies are confined to the assessment of the effects of the application of a single technology or a single course, and lack a systematic analysis of the characteristics of educational technology. These research gaps provide important entry points for this study.

2.2 Application and impact of artificial intelligence in education

The application of artificial intelligence (AI) technologies in education has become a hot research topic in recent years.Zawacki-Richter et al.'s (2019) systematic literature review on the application of AI in higher education during the period of 2007-2018 showed that AI technologies affect education in four main areas: personalised learning, intelligent tutoring systems, automated assessment and feedback, and educational management. These applications not only improve the efficiency of teaching and learning, but also provide learners with a more personalised and adaptive learning experience.

In the field of accounting education, the application of AI has started late but is developing rapidly.Guthrie and Parker (2016) point out that AI technology is reshaping the corecompetencies of the accounting profession, requiring accounting education to adapt accordingly. For example, the application of machine learning algorithms in financial statement analysis and audit risk assessment requires students to master not only traditional accounting knowledge, but also data analysis and AI application skills.The study by Issa et al. (2016) further suggests that the integration of AI technologies into the accounting curriculum can significantly improve the critical thinking and problem solving skills of students.

However, the application of AI technology in education also faces many challenges.Popenici and Kerr (2017) point out that although AI has the potential to revolutionise education, its impact in terms of ethics, privacy, and educational fairness still needs to be studied in depth. In particular, in a field like accounting, which emphasises professional ethics, how to use AI to improve teaching and learning while at the same time developing students' professional ethics and judgement has become an important research topic.

In addition, students' AI readiness plays a key role in the effective use of AI technology in education.Dwivedi et al. (2021) showed that students' attitudes towards and ability to use AI technology directly influenced their learning outcomes. However, there is still limited research on the specific mechanisms of AI readiness in accounting education, which provides an important space for exploration in this study.

2.3 Technology acceptance modelling and diffusion of innovation theory

The Technology Acceptance Model (TAM) and the Diffusion of Innovations theory provide important theoretical foundations for understanding the use and acceptance of new technologies in education.The TAM model proposed by Davis (1989) emphasises perceived usefulness and perceived ease of use as key factors influencing users' acceptance of new technologies. This model has been widely used in educational technology research, e.g. Cheung and Vogel (2013) used TAM to study the acceptance of collaborative technologies in higher education.

Diffusion of innovations theory, on the other hand, explains the process of diffusion of new technologies in society from a more macro perspective.The five characteristics of innovations (comparative advantage, compatibility, complexity, experimentability, and observability) proposed by Rogers (2003) provide a useful framework for analysing the adoption of educational technologies. For example, Zhu and Zhang (2010) used this theory to study the diffusion of e-learning systems in Chinese higher education.

In the field of accounting education, these two theories have also been widely used.Watty et al. (2016) used the TAM model to study accounting teachers' attitudes towards technological innovation and found that perceived usefulness was the main factor influencing technology adoption. While Belal et al. (2019) explored the use of big data analytics in the accounting curriculum in conjunction with the diffusion of innovation theory.

Traditional TAM models and diffusion of innovation theories have limitations in explaining the acceptance and adoption of complex technologies such as AI. In particular, these theories need to be further extended and refined when considering students' AI readiness and technology readiness. By introducing AI readiness as a mediating variable and technology readiness as a moderating variable, this study aims to construct a more comprehensive theoretical framework tobetter capture the unique impact of AI technology in accounting education.

2.4 Learning theories and digital learning environments

The emergence of digital learning environments provides new scenarios for the application and development of traditional learning theories. Social constructivist learning theory (Vygotsky, 1978) emphasises learning as a socially interactive process, an idea that has been widely validated in the design and application of online collaborative learning platforms. For example, Seaman and Tinti-Kane (2013) showed that the use of social media tools significantly enhanced collaborative learning in higher education.

In the field of accounting education, digital learning environments offer new possibilities for applying advanced learning theories.Humphrey and Beard (2014) explored how case-based online learning can promote critical thinking skills among accounting students. Their study showed that digital tools not only provide rich learning resources, but also enhance student engagement and reflection through instant feedback and collaborative features.

However, the effectiveness of digital learning environments is highly dependent on learner autonomy and self-regulation.Zimmerman's (2002) theory of self-regulated learning provides an important insight in this regard.The development of students' self-directed learning skills has become particularly important in accounting education because future accounting professionals need to be able to continuously learn and adapt to new technologies.

This study integrates these learning theoryinsights into a framework of educational technology characteristics, with a particular focus on the four dimensions of communicativeness, interactivity, mobility, and autonomy. By exploring how these characteristics affect learning outcomes and the roles that AI readiness and technology readiness play in them, this study aims to provide new theoretical perspectives and practical guidance for accounting education in the digital age.

2.5 Research gap identification

Through a systematic review of the existing literature, this study identifies the following major research gaps:

Firstly, although there has been a significant amount of research exploring the use of technology in accounting education, there is still limited research on the specific mechanisms by which AI technology affects learning outcomes. In particular, the concept of AI readiness has not yet received sufficient attention in accounting education research. Second, most of the existing studies focus on the assessment of the application effect of a single technology or a single course, and lack a systematic analysis of the characteristics of educational technology. Third, technology readiness, as an important individual difference variable, and its moderating role in the application of AI technology have not been thoroughly studied. Finally, although technology acceptance models and diffusion of innovation theories have been widely used in educational technology research, these theories have limitations in explaining the acceptance and application of complex technologies such as AI.

This study aims to fill these research gaps by constructing a comprehensive theoretical framework that integrates AI readiness and technology readiness. By systematically analysing the four educational technology characteristics of communication, interactivity, mobility and autonomy, and exploring the mediating role of AI readiness as well as the moderating role of technological readiness, this study will provide new theoretical perspectives and empirical evidence for understanding the effectiveness of AI technology in accounting education.

3. THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

3.1 Core concept definition

The theoretical framework of this study is built on four core educational technology characteristics, AI readiness and technology readiness. To ensure conceptual clarity and operational feasibility, we first define these core constructs in detail.

Communication refers to the ability of educational technology to facilitate the exchange of information and sharing of ideas. In accounting education environments, communication is reflected in the ease of instantaneous and asynchronous exchanges between students and teachers, and between students and each other through various digital tools (e.g., online discussion boards, video conferencing systems, etc.). Highly communicative educational technologies can enhance the learning experience by breaking down time and space constraints and facilitating knowledge dissemination and in-depth discussion (Arbaugh, 2000).

Interactivity reflects the extent to which users of educational technology support have two-way interactions with content, systems, or other users. In accounting education, interactivity may manifest itself as real-time feedback provided by an intelligent teaching system, role-playing exercises in a virtual simulation environment, or group projects on a collaborative platform. High interactivity helps to increase student engagement and motivation to learn, and promotes deep learning (Moore, 1989).

Mobility refers to educational technologies that support the ability of learners to learn flexibly at different times and places. In contemporary accounting education, mobility is reflected in the fact that students can access learning resources, complete assignments, or participate in discussions anytime, anywhere via mobile devices. A high degree of mobility not only provides students with greater learning freedom, but also promotes contextualised and continuous learning (Sharples et al., 2009).

Autonomy reflects the extent to which educational technology empowers learners to control and manage their own learning process. In an accounting education environment, autonomy may be expressed in the ability of students to make their own choices about the content, pace and assessment of their learning. A high level of autonomy helps to develop students' self-regulation and lifelong learning skills, which are particularly important in the fast-changing accounting profession (Zimmerman, 2002).

AI Readiness (AI Readiness) is defined as a combination of an individual's knowledge, attitudes, and ability to use AI technology. In an accounting education setting, AI readiness reflects the degree to which students understand, accept, and effectively use AI technologies for learning and problem solving. High AI readiness implies that students are not only familiar with the basic concepts and applications of AI technologies, but also actively integrate them into the learning process and recognise the importance of AI in future accounting practices (Dwivedi et al., 2021).

Technology Readiness refers to an individual's tendency toembracing and using new technologies to achieve work and life goals.Parasuraman (2000) conceptualised it as consisting of four dimensions: optimism, innovativeness, discomfort and insecurity. In the context of accounting education, high technology readiness indicates that students have a positive attitude towards new technologies, are willing to experiment with innovative learning tools, and are able to overcome challenges in the use of technology.

3.2 Hypothesis development

Based on the above definition of the core constructs and the previous literature review, the following research hypotheses were formulated:

3.2.1 Direct impact of educational technology features on learning performance

Four core characteristics of educational technology - communicative, interactive, mobile, and autonomous - are expected to positively impact the learning performance of accounting students. Highly communicative educational technologies promote effective knowledge dissemination and in-depth discussion, enhancing students' understanding of complex accounting concepts (Arbaugh & Benbunan-Fich, 2007). Highly interactive technology tools help students translate theoretical knowledge into practical skills by providing immediate feedback and opportunities for simulated practice (Evans & Gibbons, 2007). Mobility makes learning more flexible and convenient, allowing students to learn at a time and place that best suits them, thus increasing learning effectiveness (Wu et al., 2012). High autonomy, on the other hand, fosters self-regulation and active learning attitudes, which are essential for continuous learning and career development in the accounting profession (Chen, 2002). Therefore, we propose the following hypotheses:

H1: The communicative, interactive, mobile and autonomous features of educational technology are positively related to the learning performance of accounting students.

3.2.2 The mediating role of AI readiness

Although features of educational technology may directly affect learning performance, this effect is likely to be enhanced or diminished by students' AI readiness. Students with high AI readiness are more likely to take full advantage of various features of educational technology to enhance learning. For example, students with high AI readiness may be more adept at using AI-powered communication tools for effective academic discussions, better understand and apply AI-assisted interactive learning systems, more flexible in their use of AI-supported mobile learning apps, and more strategic in their use of AI technologies to manage self-directed learning processes. This mediating effect may stem from the cognitive enhancement, optimisation of learning strategies, and increased ability to apply technology as a result of AI readiness (Tran et al., 2021). Therefore, we propose:

H2: AI readiness mediates the relationship between educational technology characteristics (communicative, interactive, mobile, autonomous) and learning performance.

3.2.3 Moderating effects of technological readiness

Technology readiness, a composite indicator of an individual's attitudes and abilities toward new technologies, may moderate the mediating effect of AI readiness. Students with high technology readiness usually have a more open and positive attitude towards new technologies and are more willing to try and adapt new learning tools and methods. This tendency may reinforce the positive effects of AI readiness on the learning process. For example, students with high technology readiness may adapt to AI-driven educational technologies more quickly and integrate AI tools into their learning strategies more effectively, thus further enhancing the positive impact of AI readiness on learning performance (Parasuraman & Colby, 2015). Based on this reasoning, we propose:

H3: Technology readiness positively moderates the mediating effect of AI readiness between educational technology characteristics and learning performance, i.e., the mediating effect of AI readiness is stronger for students with higher technology readiness.

3.3 Conceptual modelling

Based on these assumptions, we constructed a comprehensive conceptual model as shown in Figure 1. The model depicts the complex relationship between educational technology characteristics (communicative, interactive, mobile, and autonomous), AI readiness, technology readiness, and learning performance.

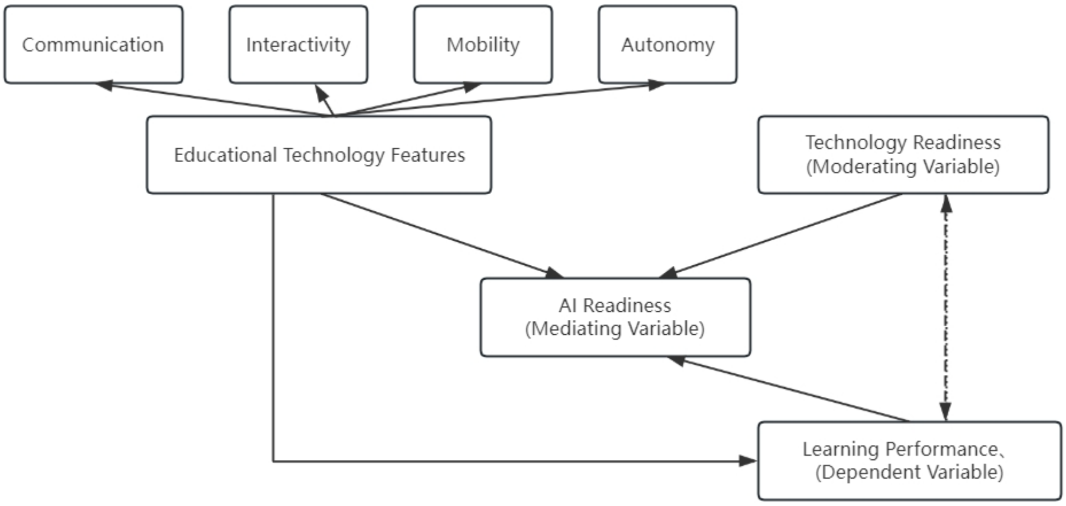

Figure 1: Integrated conceptual model

4. RESEARCH METHODOLOGY

4.1 Study design

This study adopted a mixed research methodology combining quantitative and qualitative research strategies in order to fully explore the role of AI readiness in accounting education. The primary research design was a cross-sectional questionnaire survey supplemented by focus group interviews. This mixed-methods design not only provides large samples of statistical data, but also allows for in-depth exploration of potential mechanisms and explanations through qualitative data (Creswell & Plano Clark, 2017). Questionnaires were designed to collect quantitative data on educational technology characteristics, AI readiness, technology readiness, and learning performance to validate the proposed research hypotheses. Focus group interviews were used to complement the quantitative analyses by providing in-depth explanations and insights into the results. Through this combination of methods, we expect to obtain more comprehensive and in-depth findings that will enhance the credibility and usefulness of the study's conclusions.

4.2 Sample selection and data collection

The object of the study is undergraduate accounting students in mainland China. Stratified random sampling method was used to select samples from colleges and universities of different regions and types (comprehensive universities, finance and economics colleges) to ensure the representativeness and diversity of the samples. Considering the requirements of structural equation modelling analysis, model complexity and expected effect size, the target sample size was set at 1000 students (Hair et al., 2010). The data collection process was divided into two stages: firstly, links to the online questionnaire were distributed through the academic systems and student organisations of each university, using a lottery incentive mechanism to increase the response rate; secondly, 30 students were selected from the questionnaire respondents to form five focus groups (six per group) for semi-structured interviews. Selection criteria included AI readiness score (high, medium, and low), academic year (freshman to senior), and gender balance to ensure richness and representativeness of the interview data. Data collection was scheduled for the Spring 2024 semester (March to May), a time period chosen to ensure that students had sufficient time to experience and evaluate various educational technologies, thus providing more accurate and valuable feedback.

4.3 Measurement of variables

All variables in this study were measured on a 7-point Likert scale (1=strongly disagree, 7=strongly agree), and all variables except learning performance were self-report measures. Educational technology characteristics were used as independent variables and included four dimensions: communicative, interactive, mobile, and autonomous. Communicativeness was measured using Arbaugh and Benbunan-Fich's (2007) scale containing five question items; interactiveness was based on a modification of Evans and Gibbons' (2007) scale containing six question items; mobility was developed with four question items with reference to Sharples et al.'s (2009) study; and autonomy was based on Chen (2002)'s Autonomous Learning Scale, which contains 5 question items. The selection and modification of these scales aimed to comprehensively capture the key features of educational technology in accounting education.

The dependent variable learning performance was measured using a multidimensional approach that included objective academic performance (final exam grades and semester GPA), subjective learning satisfaction (using Arbaugh's (2000) scale with 6 items), and perceived learning gains (based on Alavi's (1994) scale with 5 items). This multidimensional measure allows for a more comprehensive assessment of learning outcomes, encompassing not only traditional academic performance, but also students' subjective perceptions and competence enhancement.

The mediator variable AI readiness was based on a modification of Parasuraman's (2000) Technology Readiness Index (TRI), which developed a 12-item scale covering the dimensions of AI perceptions, AI attitudes, and AI usability. The moderator variable Technology Readiness was developed using Parasuraman and Colby's (2015) revised TRI 2.0 scale containing 16 items measuring the four dimensions of optimism, innovativeness, discomfort, and insecurity. The selection and development of these scales ensured accurate measurement of two key constructs, AI readiness and technology readiness.

4.4 Methods of statistical analyses

Data analysis will be carried out using SPSS 28.0 and AMOS 28.0 software, employing a range of rigorous statistical methods to ensure the reliability and validity of the results. Firstly, descriptive statistical analyses and correlation analyses will be carried out to gain a preliminary understanding of the distributional characteristics and interrelationships of the variables. Subsequently, the reliability and validity of the scale will be comprehensively tested by calculating the Cronbach's alpha coefficient, conducting exploratory factor analysis (EFA) and validation factor analysis (CFA), and calculating the average variance extracted (AVE).

The validation of the research hypotheses is mainly achieved through structural equation modelling (SEM). We adopt the two-stage approach proposed by Anderson and Gerbing (1988) to confirm the fit of the measurement model before validating the hypothesised model. Model fit goodness of fit will be assessed by several metrics including χ^2/df, CFI, TLI, RMSEA, and SRMR.For the test of mediating effects, we will use the Bootstrap method (5000 repetitions of sampling) to calculate the direct, indirect, and total effects. The moderating effect of technology readiness is tested by the latent variable interaction method (LMS) (Klein & Moosbrugger, 2000). In order to fully analyse the strength of the mediating effect of AI readiness at different levels of technology readiness, we will use the integration method proposed by Edwards and Lambert (2007).

To ensure the robustness of the findings, a number of additional analyses will be conducted. These include a common method bias test (using the Harman one-way test and latent method factorial), a multi-cluster invariance test (to assess the cross-group stability of the model), and alternative model comparisons. Qualitative data analyses will be conducted using a thematic coding approach, using NVivo 12 software to aid analysis and distil key themes and patterns through open coding, axial coding and selective coding.

Through these rigorous statistical analysis methods, we expect to fully validate the research hypotheses and provide in-depth insights. At the same time, complementary analyses of qualitative data will help explain the quantitative results and enhance the credibility and usefulness of the research findings. This combination of quantitative and qualitative methods will not only validate the theoretical models, but also provide insights into the specific applications and impact mechanisms of AI and technology in accounting education, which will provide strong support for future educational practices and policy development.

5. DATA ANALYSIS AND RESULTS

5.1 Descriptive statistical results

In the end, 985 valid questionnaires were collected for this study, with a valid return rate of 98.5 per cent. The basic characteristics of the sample are shown in Table 1, reflecting the distribution of participants in terms of gender, grade level and type of school.

Table 1: Basic characteristics of the sample (N = 985)

Diagnostic property	Form	Frequency	Percentage (%)
Distinguishing between the sexes	male	451	45.8
	women	534	54.2
Grade	first-year university student	231	23.5
	second-year university student	279	28.3
	third-year university student	263	26.7
	fourth-year university student	212	21.5
Type of school	comprehensive university	594	60.3
	finance and economics college	391	39.7

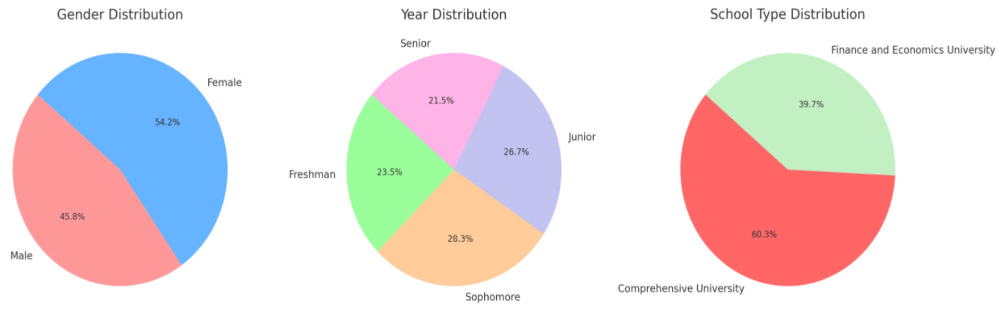

Figure 2: Pie chart of basic characteristics of the sample

The descriptive statistics of the main study variables are shown in Table 2. The results show that the mean, standard deviation, skewness and kurtosis of the variables are within acceptable limits, indicating a more normal distribution of data.

Table 2: Descriptive statistics of the main study variables (N = 985)

Variant	(statistics) Standard deviation	Skewness	Kurtosis
Communicative	1.21	-0.62	0.18
Interactive	1.08	-0.75	0.43

Mobility	1.15	-0.68	0.25
Autonomy	1.26	-0.54	-0.07
AI readiness	1.33	-0.32	-0.41
Technology readiness	1.17	-0.48	0.05
Perceived Learning Gains	1.09	-0.59	0.21
Learning satisfaction	1.14	-0.51	0.09
Objective Learning Achievement	0.89	-0.23	-0.18

Note: Objective learning outcomes have been standardised.

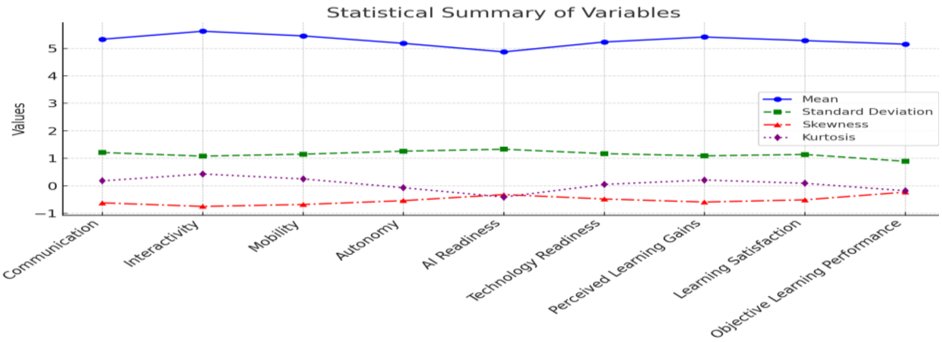

Figure 3: Descriptive statistics line graphs of the main study variables

5.2 Evaluation of measurement models

The results of the reliability analysis of the measurement model are shown in Table 3. The Cronbach's alpha coefficient and composite reliability (CR) values for all latent variables exceeded the recommended thresholds, indicating that the scale has good internal consistency. The average variance extracted (AVE) values were all higher than 0.50, supporting the convergent validity of the scale.

Table 3: Results of the reliability analysis of the measurement model

Latent variable	Cronbach's α	CR	AVE
Communicative	0.892	0.921	0.701
Interactive	0.905	0.928	0.683
Mobility	0.884	0.915	0.729
Autonomy	0.876	0.907	0.662
AI readiness	0.923	0.938	0.654
Technology readiness	0.897	0.919	0.591
Learning performance	0.912	0.934	0.702

The goodness-of-fit metrics for the measurement model were as follows: $\chi^2/df = 2.37$, CFI = 0.956, TLI = 0.948, RMSEA = 0.041 (90% CI: [0.036, 0.046]), and SRMR = 0.035. These metrics were all at or better than the recommended thresholds, indicating that the measurement model had good construct validity.

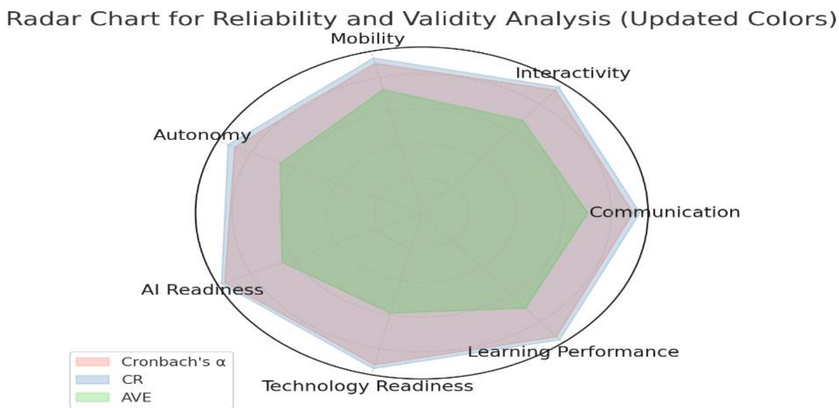

Figure 4: Radar diagram of the reliability analysis of the measurement model

5.3 Structural modelling analysis

The goodness-of-fit metrics for the structural model also showed good model fit: $\chi^2/df = 2.53$, CFI = 0.947, TLI = 0.939, RMSEA = 0.044 (90% CI: [0.039, 0.049]), SRMR = 0.038. The results of the path analysis are shown in Table 4.

Table 4: Structural model path analysis results

Trails	Standardised coefficient	t-value	p-value
Communicative → Learning Performance	0.253	5.874	<0.001
Interactivity → Learning Performance	0.315	7.236	<0.001
Mobility → Learning Performance	0.287	6.592	<0.001
Autonomy → learning performance	0.226	5.189	<0.001
AI readiness → learning performance	0.342	7.853	<0.001

5.4 Mediated effects test

The results of the mediation effect test for AI readiness are shown in Table 5.The results of the Bootstrap method (5,000 replicated samples) support a partial mediation effect of AI readiness.

Table 5: Results of the mediation effect analysis of AI readiness

Trails	Indirect effect	95% CI	p-value
Communicative → AI readiness → Learning performance	0.108	[0.069, 0.147]	<0.001
Interactivity → AI Readiness → Learning Performance	0.142	[0.098, 0.186]	<0.001
Mobility → AI Readiness → Learning Performance	0.124	[0.083, 0.165]	<0.001
Autonomy → AI readiness → learning performance	0.095	[0.058, 0.132]	<0.001

5.5 Analysis of moderating effects

The results of the moderating effect analysis of technology readiness are shown in Table 6. The results of the latent variable interaction method (LMS) support the significant moderating effect of technology readiness.

Table 6: Results of the analysis of the moderating effect of technological readiness

Interaction term	Standardised coefficient	t-value	p-value
AI readiness × technology readiness	0.176	3.842	<0.01

Simple slope analyses further reveal specific patterns of moderating effects:

High technology readiness group: $\beta = 0.453$, $p < 0.001$

Low technology readiness group: $\beta = 0.277$, $p < 0.001$

These results suggest that technology readiness enhances the positive effect of AI readiness on learning performance.

5.6 Robustness tests

The reliability of the findings is further supported by the results of the robustness test.The Harman one-way test shows that the first unrotated factor explains 28.7 per cent of the variance, which is lower than the 50 per cent threshold, suggesting that common method bias is not a major problem. The results of the multi-group invariance test, shown in Table 7, support the stability of the model across groups.

Table 7: Results of invariance test for multiple clusters

Modelling	χ^2/df	CFI	ΔCFI	RMSEA	ΔRMSEA
Configuration invariance	2.41	0.946	-	0.042	-
metric invariant (math.)	2.45	0.943	0.003	0.043	0.001
scalar invariant (math.)	2.49	0.940	0.003	0.044	0.001
residual invariance	2.52	0.938	0.002	0.045	0.001

Note: ΔCFI < 0.01 and ΔRMSEA < 0.015 indicate that invariance holds.

These findings not only validate the theoretical model proposed in this study, but also provide insights into understanding the application of AI technology in accounting education and its influencing factors. The results of the qualitative analyses are highly consistent with these quantitative findings, further enhancing the credibility and practical value of the study's conclusions.

6. DISCUSSION

6.1 Key findings

The purpose of this study was to explore the role of AI readiness in accounting education, with a particular focus on its mediating role between educational technology characteristics and learning performance, as well as the moderating effect of technology readiness. The results of the study reveal several important findings that provide new insights into understanding the use of AI technology in accounting education. First, all four core features of educational technology - communicative, interactive, mobile, and autonomous - had a significant positive effect on accounting students' learning performance. This finding is consistent with the established literature on the positive effects of educational technology on learning outcomes (e.g., Arbaugh & Benbunan-Fich, 2007; Evans & Gibbons, 2007). Of particular note was the most significant effect of interactivity ($\beta = 0.315$, $p < 0.001$), which emphasises the importance of creating an interactive learning environment in accounting education. This may reflect the nature of the accounting discipline, which requires a great deal of practice and application to master complex concepts and skills. Secondly, the study confirmed the partial mediating role of AI readiness between educational technology characteristics and learning performance. This finding extends Dwivedi et al.'s (2021) research on the role of AI in education by explicitly identifying AI readiness as a key mechanism linking educational technology and learning outcomes. Specifically, AI readiness had the strongest mediating effect between interactivity and learning performance (indirect effect = 0.142, 95% CI: [0.098, 0.186]), suggesting that students' AI readiness is particularly important for making the most of interactive educational technologies. Third, technology readiness was shown to have a significant positive moderating effect on the relationship between AI readiness and learning performance ($\beta = 0.176$, $p < 0.01$). This finding echoes Parasuraman and Colby's (2015) thesis that technology readiness influences technology adoption, but further reveals the specific mechanism of its action in the context of AI. For students with high technology readiness, the effect of AI readiness on learning performance was stronger (β high = 0.453 vs. β low = 0.277), implying that increasing students' overall technology readiness may be an effective strategy for enhancing the effects of AI education.

6.2 Theoretical contributions

This study makes several important theoretical contributions to the existing literature that expand our understanding of the application of AI technology in accounting education. By introducing the new variable of AI readiness, this study expands the application of the Technology Acceptance Model (TAM) and Diffusion of Innovations Theory in accounting education. This extension is particularly applicable to explaining the process of acceptance and impact of emerging AI technologies in education, providing a richer theoretical framework for understanding technology adoption and effectiveness in education. This study fills a theoretical gap in prior research by clarifying the role of AI readiness as a mediating mechanism. This finding not only explains why the same educational technology may lead to different learning outcomes, but also emphasises the importance of fostering students' AI readiness during technology implementation. By examining the moderating role of technology readiness, this study further deepens the understanding of the complex mechanisms underlying the use of technology in education. This finding highlights the importance of individual differences in technology adoption and effectiveness and provides new theoretical perspectives for future research. In addition, this study integrates the four dimensions of communicativeness, interactivity, mobility, and autonomy to propose a more comprehensive framework for assessing the characteristics of educational technology. This framework is not only applicable to accounting education, but may also be extended to other subject areas, providing a new analytical tool for educational technology research.

6.3 Practical implications

The findings of this study have important implications for accounting education practice and provide valuable guidance for educators and policy makers. The findings of the study emphasise the importance of educational technology, especially interactive features, on learning performance. This suggests that accounting educators should prioritise the adoption of technological tools and platforms that can facilitate teacher-student and student-student interactions. For example, intelligent AI-based question and answer systems or virtual simulation environments could be introduced to enhance the interactivity of courses. Given the critical mediating role of AI readiness, colleges and universities should systematically enhance students' AI literacy. This may include offering AI foundation courses, organising AI application workshops, or integrating the use of AI tools into existing accounting courses, and attention should be paid to the training of teachers in AI competencies to ensure that they are able to effectively guide students in the use of AI technologies. The moderating effect of technology readiness suggests that improving students' overall technological literacy can enhance the effectiveness of AI education. Colleges and universities can consider setting up digital literacy training programmes covering basic technology skills, information literacy, and data analytics to prepare students for the accounting work environment in the AI era. The study found differences in AI readiness and technology readiness among students, suggesting that educators should adopt more personalised teaching strategies. For example, AI tasks of varying difficulty or additional support resources could be provided to meet the needs of different students based on their level of technology readiness.

6.4 Limitations of the study

Although this study provided valuable findings, there are some limitations that also point the way to future research. The cross-sectional study design limits inferences of causality, and our theoretical model is based on existing literature and logical reasoning, but cannot completely rule out the possibility of reverse causality. Future studies may consider adopting a longitudinal design or experimental approach to better establish causal relationships among variables. The sample of this study was limited to accounting students in mainland China, which may limit the generalisability of the findings. Different cultural backgrounds and education systems may affect how AI technology is accepted and used, so a cross-cultural comparative study may provide richer insights. Measures of learning performance were largely based on self-reports, which may be subjectively biased. Although we adopted a multidimensional measurement approach, including objective learning performance, future research could consider incorporating more objective indicators of learning outcomes, such as standardised test scores or vocational skills assessments, to enhance the reliability of the measure. Finally, this study focused on AI readiness but did not delve into its specific components. Future research could further refine the dimensions of AI readiness, such as AI cognition, AI attitudes, and AI skills, to provide a more refined understanding and intervention strategies.

6.5 Directions for future research

Based on the findings and limitations of this study, we propose several research directions that deserve further exploration. Future research could explore the formation mechanism of AI readiness in depth and investigate the antecedent factors affecting students' AI readiness, such as personal traits, learning experiences, and social influences, in order to develop more targeted AI education strategies. Second, considering the diversity of accounting disciplines, future research can compare the application and effect differences of AI in different courses, such as financial accounting, management accounting, and auditing, to provide more specific guidance for curriculum design. With the development of AI technology, the skills needed by accounting professionals may change, so it is also an important direction to study the impact of AI on the core competencies of the accounting profession. The role of teacher factors in AI education deserves further exploration. Teachers' AI literacy and teaching philosophy may significantly affect students' AI readiness and learning outcomes, and future research could incorporate teacher factors into the model to explore their moderating or mediating role. Considering the context of globalisation, a cross-cultural comparative study could reveal the role of cultural factors in AI education and provide valuable insights into internationalised accounting education.

This study provides an important theoretical and empirical basis for understanding the role of AI technology in accounting education. With the continuous development of AI technology, future research needs to continue to focus on this area to provide a scientific basis and practical guidance for the cultivation of high-quality accounting talents adapted to the intelligent era. Through continued research and practical innovation, we can better utilise the potential of AI technology to improve the quality and relevance of accounting education and pave the way for the future training of accounting professionals.

7. CONCLUSION

This study examines the critical role of AI readiness in accounting education, focusing specifically on its mediating role between educational technology characteristics and learning performance, as well as the moderating effect of technology readiness. Through a survey of 985 undergraduate accounting students in mainland China, this study not only verified the direct effects of educational technology features (communicative, interactive, mobile and autonomous) on learning performance, but also revealed the importance of AI readiness as a key mediating mechanism. Interactivity was found to have the most significant effect on learning performance, and AI readiness had the strongest mediating effect between interactivity and learning performance. In addition, technology readiness was shown to enhance the positive effect of AI readiness on learning performance, highlighting the importance of improving students' overall technological literacy.

These findings have important implications for both theory and practice in accounting education. On the theoretical front, this study extends the application of the technology acceptance model and the diffusion of innovation theory in the context of AI education by proposing a new framework for integrating AI readiness. This framework not only helps to explain the acceptance and effects of AI technology in education, but also provides new theoretical perspectives for future research. On the practical side, the findings provide valuable guidance for accounting educators and policy makers. The importance of increasing interactivity in curriculum design is highlighted, systematic efforts to enhance students' AI literacy are recommended, and more personalised teaching strategies are called for to accommodate differences in students' AI and technology readiness.

Although there are some limitations in this study, such as the cross-sectional design limiting causal inference and the sample being confined to mainland China may affect the generalisability of the results, these limitations also point the way for future research. Future research could consider a longitudinal design or an experimental approach to explore cross-cultural comparisons, to investigate in depth the mechanisms that shape AI readiness, and to examine the impact of AI on the core COMPETENCIES of the accounting profession.

This study provides an important theoretical and empirical foundation for understanding the role of AI technology in accounting education. As AI technology continues to be deeply applied in the accounting industry, it has become increasingly important to cultivate high-quality accounting talents with AI literacy. The findings of this study not only help to optimise current accounting education practices, but also provide a scientific basis for future curriculum design and education policy development. By continuing to pay attention to the application of AI technology in education and actively addressing the challenges and opportunities it brings, we can better cultivate accounting professionals who are adapted to the smart era and promote the common development of accounting education and the accounting industry.

REFERENCES

Apostolou, B., Dorminey, J. W., Hassell, J. M., & Rebele, J. E. (2019). Accounting education literature review (2018). Journal of Accounting Education, 47, 1-27. https://doi.org/10.1016/j.jaccedu.2019.02.001

Arbaugh, J. B. (2000). Virtual classroom characteristics and student satisfaction with internet-based MBA courses. Journal of Management Education, 24(1), 32-54. https://doi.org/10.1177/105256290002400104

Arbaugh, J. B., & Benbunan-Fich, R. (2007). The importance of participant interaction in online environments. Decision Support Systems, 43(3), 853-865. https://doi.org/10.1016/j.dss.2006.12.013

Belal, A. R., Abdelsalam, O., & Nizamee, S. S. (2019). Ethical reporting in Islami Bank Bangladesh Limited (1983-2010). Journal of Business Ethics, 156(1), 85-104. https://doi.org/10.1007/s10551-017-3581-8

Chen, C. S. (2002). Self-regulated learning strategies and achievement in an introduction to information systems course. Information Technology, Learning, and Performance Journal, 20(1), 11-25.

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: an extension of the technology acceptance model for e-learning. Computers & Education Computers & Education , 63, 160-175. https://doi.org/10.1016/j.compedu.2012.12.003

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

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Evans, C., & Gibbons, N. J. (2007). The interactivity effect in multimedia learning. Computers & Education, 49(4), 1147-1160. https://doi.org/10.1016/j.compedu.2006.01.008

Guthrie, J., & Parker, L. D. (2016). Whither the accounting profession, accountants and accounting researchers? Commentary and projections. Accounting, Auditing & Accountability Journal, 29(1), 2-10. https://doi.org/10.1108/AAAJ-10-2015-2263

Holtzblatt, M., & Tschakert, N. (2011). Expanding your accounting classroom with digital video technology. Journal of Accounting Education, 29(2-3), 100-121. https://doi.org/10.1016/j.jaccedu.2011.10.003

Humphrey, R. L., & Beard, D. F. (2014). Faculty perceptions of online homework software in accounting education. Journal of Accounting Education, 32(3), 238-258. https://doi.org/10.1016/j.jaccedu.2014.06.001

Issa, T., Selamat, M. H., & Muthuveloo, R. (2016). A conceptual framework on the relationship between artificial intelligence (AI) and accounting education. Journal of Management Research, 8(3), 1-13 . https://doi.org/10.5296/jmr.v8i3.9373

Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. Journal of Emerging Technologies in Accounting, 14(1), 115-122. https://doi.org/10.2308/jeta-51730

Liang, S., Rajora, M., Liu, X., Yue, C., Zou, P., & Wang, L. (2022). Intelligent manufacturing systems: A review. International Journal of Mechanical Engineering and Robotics Research, 11(1), 8-15. https://doi.org/10.18178/ijmerr.11.1.8-15

Moore, M. G. (1989). Editorial: three types of interaction. American Journal of Distance Education, 3(2), 1-7. https://doi.org/10.1080/08923648909526659

Parasuraman, A. (2000). Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. Journal of Service Research, 2(4), 307-320. Journal of Service Research, 2(4), 307-320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: the TRI 2.0. Journal of Service Research, 18(1), 59-74. https://doi.org/10.1177/1094670514539730

Pincus, K. V., Stout, D. E., Sorensen, J. E., Stocks, K. D., & Lawson, R. A. (2017). Forces for change in higher education and implications for the accounting academy. Journal of Accounting Education, 40, 1-18. https://doi.org/10.1016/j.jaccedu.2017.06.001

Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. research and Practice in Technology Enhanced Learning,. 12(1), 1-13. https://doi.org/10.1186/s41039-017-0062-8

Quattrone, P. (2016). Management accounting goes digital: will the move make it wiser? Management Accounting Research, 31, 118-122. https://doi.org/10.1016/j.mar.2016.01.003
Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.
Seaman, J. E., & Tinti-Kane, H. (2013). Social media for teaching and learning. Pearson Learning Solutions and Babson Survey Research Group.
Sharples, M., Arnedillo-Sánchez, I., Milrad, M., & Vavoula, G. (2009). Mobile learning. in N. Balacheff, S. Ludvigsen, T. de Jong, A. Lazonder, & S. Barnes (Eds.), Technology-enhanced learning (pp. 233-249). Springer. https://doi.org/10.1007/978-1-4020-9827-7_14
Sledgianowski, D., Gomaa, M., & Tan, C. (2017). Toward integration of Big Data, technology and information systems competencies into the accounting curriculum. Journal of Accounting Education, 38,. 81-93. https://doi.org/10.1016/j.jaccedu.2016.12.008
Tran, T., Huu Ho, T., Vargas Palma, C., Nguyen, M., & Nguyen, H. (2021). Impact of artificial intelligence on student learning outcomes in accounting courses: an empirical study in Vietnam. sustainability, 13(14), 7746. https://doi.org/10.3390/su13147746
Vygotsky, L. S. (1978). Mind in society: The development of higher psychological processes. Harvard University Press.
Watty, K., McKay, J., & Ngo, L. (2016). Innovators or inhibitors? Accounting faculty resistance to new educational technologies in higher education. Journal of Accounting Education, 36, 1- 15. https://doi.org/10.1016/j.jaccedu.2016.03.003
Wu, W. H., Wu, Y. C. J., Chen, C. Y., Kao, H. Y., Lin, C. H., & Huang, S. H. (2012). Review of trends from mobile learning studies: a meta-analysis. Computers & Education, 59(2), 817-827. https://doi.org/10.1016/j.compedu.2012.03.016
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. https://doi.org/10.1186/s41239-019-0171-0
Zhu, C., & Zhang, J. (2010). Diffusion of e-learning in Chinese universities: A perspective of students. Chinese Journal of Distance Education, 5, 66-70.
Zimmerman, B. J. (2002). Becoming a self-regulated learner: an overview. Theory Into Practice, 41(2), 64-70. https://doi.org/10.1207/s15430421tip4102_2
Alavi, M. (1994). Computer-mediated collaborative learning: an empirical evaluation. MIS Quarterly, 18(2), 159-174. https://doi.org/10.2307/249763
Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modelling in practice: a review and recommended two-step approach. Psychological Bulletin, 103(3), 411-423. https://doi.org/10.1037/0033-2909.103.3.411
Arbaugh, J. B. (2000). Virtual classroom characteristics and student satisfaction with internet-based MBA courses. Journal of Management Education, 24(1), 32-54. https://doi.org/10.1177/105256290002400104
Arbaugh, J. B., & Benbunan-Fich, R. (2007). The importance of participant interaction in online environments. Decision Support Systems, 43(3), 853-865. https://doi.org/10.1016/j.dss.2006.12.013
Chen, C. S. (2002). Self-regulated learning strategies and achievement in an introduction to information systems course. Information Technology, Learning, and Performance Journal, 20(1), 11-25.
Creswell, J. W., & Plano Clark, V. L. (2017). Designing and conducting mixed methods research (3rd ed.). Sage Publications.
Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
Edwards, J. R., & Lambert, L. S. (2007). Methods for integrating moderation and mediation: a general analytical framework using moderated path analysis. Psychological Methods, 12(1), 1-22. https://doi.org/10.1037/1082-989X.12.1.1
Evans, C., & Gibbons, N. J. (2007). The interactivity effect in multimedia learning. Computers & Education, 49(4), 1147-1160. https://doi.org/10.1016/j.compedu.2006.01.008

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Prentice Hall.

Klein, A., & Moosbrugger, H. (2000). Maximum likelihood estimation of latent interaction effects with the LMS method. psychometrika, 65(4), 457-474. https://doi.org/10.1007/BF02296338

Parasuraman, A. (2000). Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. Journal of Service Research, 2(4), 307-320. Journal of Service Research, 2(4), 307-320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: the TRI 2.0. Journal of Service Research, 18(1), 59-74. https://doi.org/10.1177/1094670514539730

Sharples, M., Arnedillo-Sánchez, I., Milrad, M., & Vavoula, G. (2009). Mobile learning. in N. Balacheff, S. Ludvigsen, T. de Jong, A. Lazonder, & S. Barnes (Eds.), Technology-enhanced learning (pp. 233-249). Springer. https://doi.org/10.1007/978-1-4020-9827-7_14