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NAVIGATING THE FUTURE: EXPLORING AI ADOPTION IN CHINESE HIGHER EDUCATION THROUGH THE LENS OF DIFFUSION THEORY

Qiubo Huang	School of Economics and Social Welfare, Zhejiang Shuren University, Hangzhou, Zhejiang Province, China	qiubo_huang@zjsru.edu.cn
Pivithuru Janak Kumarasinghe *	School of Economics and Social Welfare, Zhejiang Shuren University, Hangzhou, Zhejiang Province, China	janak_kumarasighe@zjsru.edu.cn
Gothami Sakunthala Jayarathna	Faculty of Management, University of Sri Jayewardenepura, Sri Lanka	gothami.usjp@gmail.com

* Corresponding author

ABSTRACT

Aim/Purpose	This paper aims to investigate and understand the intentions of management undergraduate students in Hangzhou, China, regarding the adoption of Artificial Intelligence (AI) technologies in their education. It addresses the need to explore the factors influencing AI adoption in the educational context and contribute to the ongoing discourse on technology integration in higher education.
Background	The paper addresses the problem by conducting a comprehensive investigation into the perceptions of management undergraduate students in Hangzhou, China, regarding the adoption of AI in education. The study explores various factors, including Perceived Relative Advantage and Trialability, to shed light on the nuanced dynamics influencing AI technology adoption in the context of higher education.
Methodology	The study employs a quantitative research approach, utilizing the Confirmatory Tetrad Analysis (CTA) and Partial Least Squares Structural Equation Modeling (PLS-SEM) methodologies. The research sample consists of management

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	undergraduate students in Hangzhou, China, and the methods include data screening, principal component analysis, confirmatory tetrad analysis, and evaluation of the measurement and structural models. We used a random sampling method to distribute 420 online, self-administered questionnaires among management students aged 18 to 21 at universities in Hangzhou.
Contribution	This paper explores how management students in Hangzhou, China, perceive the adoption of AI in education. It identifies factors that influence AI adoption intention. Furthermore, the study emphasizes the complex nature of technology adoption in the changing educational technology landscape. It offers a thorough comprehension of this process while challenging and expanding the existing literature by revealing the insignificant impacts of certain factors. This highlights the need for an approach to AI integration in education that is context-specific and culturally sensitive.
Findings	The study highlights students' positive attitudes toward integrating AI in educational settings. Perceived relative advantage and trialability were found to impact AI adoption intention significantly. AI adoption is influenced by social and cultural contexts rather than factors like compatibility, complexity, and observability. Peer influence, instructor guidance, and the university environment were identified as pivotal in shaping students' attitudes toward AI technologies.
Recommendations for Practitioners	To promote the use of AI among management students in Hangzhou, practitioners should highlight the benefits and the ease of testing these technologies. It is essential to create communication strategies tailored to the student's needs, consider cultural differences, and utilize the influence of peers and instructors. Establishing a supportive environment within the university that encourages innovation through policies and regulations is vital. Additionally, it is recommended that students' attitudes towards AI be monitored constantly, and strategies adjusted accordingly to keep up with the changing technological landscape.
Recommendations for Researchers	Researchers should conduct cross-disciplinary and cross-cultural studies with qualitative and longitudinal research designs to understand factors affecting AI adoption in education. It is essential to investigate compatibility, complexity, observability, individual attitudes, prior experience, and the evolving role of peers and instructors.
Impact on Society	The study's insights into the positive attitudes of management students in Hangzhou, China, toward AI adoption in education have broader societal implications. It reflects a readiness for transformative educational experiences in a region known for technological advancements. However, the study also underscores the importance of cautious integration, considering associated risks like data privacy and biases to ensure equitable benefits and uphold educational values.
Future Research	Future research should delve into AI adoption in various academic disciplines and regions, employing longitudinal designs and qualitative methods to understand cultural influences and the roles of peers and instructors. Investigating moderating factors influencing specific factors' relationship with AI adoption intention is essential for a comprehensive understanding.

Keywords	AI integration in education, Chinese university education, student perspectives, diffusion theory, PLS-SEM analysis

INTRODUCTION

The integration of artificial intelligence assisted learning (AIAL) in universities worldwide is rapidly increasing to enhance the learning experience for students. AIAL utilizes artificial intelligence to identify valuable patterns and insights, thereby improving education (Alkhulaifat et al., 2023; Tam et al., 2023; X. Wang et al., 2023). This innovative approach can revolutionize undergraduate education, impacting both students' learning experiences and educators' teaching methods (Keiper et al., 2023; Tam et al., 2023). With rapidly evolving artificial intelligence (AI) technologies, numerous opportunities exist to personalize learning and improve academic outcomes (Chatterjee & Bhattacharjee, 2020). Understanding the factors influencing undergraduate students' readiness to embrace AI technologies is crucial as it prepares them for an AI-integrated future (Alkhulaifat et al., 2023; Chiu et al., 2023).

This research focuses on AI integration in undergraduate management education in Hangzhou, China. Hangzhou, known for its innovative higher education institutions, blends tradition with technological advancement (Hao, 2019). Its strategic location enhances the relevance and transferability of findings. Through a survey at prominent universities in Hangzhou, this study aims to uncover factors influencing the acceptance of AI technology among undergraduate students. AI technologies offer tailored learning experiences and data-driven insights, potentially enhancing pedagogical strategies (Alkhulaifat et al., 2023; Lakshmi et al., 2023). However, their impact depends on various adoption and utilization factors among students. Further, the study aims to identify key factors influencing AI technology use among students and understand their perceptions and attitudes. The insights from this study can inform education professionals, policymakers, and technology developers, ultimately improving the quality of education and fostering progress in the field.

Our research aims to emphasize the potential of AIAL in management studies. While AI has transformative potential across various academic disciplines, management education presents unique challenges and opportunities that require special attention. The field of management encompasses a wide range of topics, including leadership, decision-making, and organizational behavior, which require tailored approaches to teaching and learning. By focusing on management education, we can explore how AIAL can be adapted to address the distinct needs of management students, such as real-world problem solving, strategic thinking, and teamwork skills development. This unique focus enables us to uncover insights that may be absent in other academic domains. This contributes to a more comprehensive understanding of how AI is adopted in higher education management. By selecting undergraduate students over graduate students, the research aims to capture early-stage perceptions and attitudes toward AI adoption, which can inform educational practices and policies from the undergraduate level upwards. The choice of this specific demographic was intentional, considering China's significant advancements in AI technology and its impact on higher education. Hangzhou embodies a higher education ecosystem that seamlessly blends age-old customs with an unwavering dedication to technological advancement. Further, Hangzhou's strategic location in China, with easy access to major urban centers and technology hubs, adds value to our findings by enhancing their relevance and transferability. Through a survey conducted at prominent universities in Hangzhou, the study aims to uncover the intricate interplay of factors that impact the acceptance and implementation of AIAL among undergraduate students.

LITERATURE REVIEW

AI involves machines, particularly computer systems, simulating human intelligence processes. These processes encompass learning, reasoning, problem-solving, perception, and language understanding. In the field of education, AI can be utilized to customize learning experiences, forecast student performance, and offer immediate feedback, among other uses (Alhazmi et al., 2023; Dai & Ke, 2022). Despite AI's growing importance in education, the landscape of its adoption in higher education remains complex and multifaceted (Crompton & Burke, 2023). The adoption of AI in education is a multifaceted process that involves not only integrating AI technologies into teaching and learning practices but also the acceptance of these technologies by students and educators. The scope of AI adoption for learning purposes can range from using AI-powered educational apps and platforms to implementing AI in administrative processes in educational institutions (Ahmad et al., 2020; Alhazmi et al., 2023; Miao et al., 2021). In order to fully utilize AI in education, it is crucial to understand the factors that influence the willingness and perceived value of students to embrace advanced technologies such as AI in their educational environment. AI technology has immense potential to transform undergraduate management education in various ways. AI can revolutionize personalized learning by analyzing student data and creating educational pathways tailored to each individual's unique needs. This level of customization enhances the learning experience and makes it more engaging and effective for undergraduate students. Additionally, AIAL can predict learning outcomes and enable educators to identify students requiring additional support, leading to improved educational outcomes. AI can support students with special requirements through adaptive learning systems and assistive technologies, helping them overcome learning barriers and achieve their full potential.

Additionally, AIAL ensures that management students have seamless access to essential materials and support for better educational outcomes (Ratten & Jones, 2023). Furthermore, AI can assist in creating customized curricula tailored to individual students' needs and provide real-time feedback during the learning process (Seo et al., 2021). This immediate response can help students understand their strengths and weaknesses, enabling them to focus on areas that need improvement (Chaudhry & Kazim, 2022). AI's capabilities can significantly enhance undergraduate management education and improve educational outcomes (Keiper et al., 2023). These innovative tools can significantly enhance teaching strategies, but their impact on education depends on various factors that can influence student adoption and utilization. Several studies have explored the adoption of AIAL in education from various perspectives. For example, Dahri et al. (2024) examined the factors influencing students' acceptance of AI-powered educational apps, while Slimi (2023) investigated the impact of AI on teaching practices in higher education. Labadze et al. (2023) conducted a comprehensive review of the literature on AIAL in education, highlighting the potential benefits and challenges of AI adoption in educational settings. Further, studies have researched the application of AIAL in education. For example, Jang et al. (2022), Ouyang et al. (2023), and Tam et al. (2023) investigated how AIAL can personalize learning experiences in higher education, while Jang et al. (2022) examined the use of AIAL in predicting student performance. These studies have found that AI can significantly enhance the learning experience by providing personalized learning pathways and real-time feedback, improving educational outcomes. Furthermore, Parycek et al. (2023) and Holstein and Doroudi (2021) conducted a study on the use of AI in administrative processes in academic institutions, highlighting the potential of AIAL to streamline administrative tasks and improve efficiency. These studies emphasize the transformative potential of AIAL in education and its growing importance in the field.

Given the complexity of AI in higher education, this research aims to delve into the factors influencing undergraduate students' acceptance and adaptation of AIAL in their management education, specifically focusing on the context of Hangzhou, China. In exploring the intention of management undergraduate students to use AIAL technologies in undergraduate studies, the researchers have chosen the Diffusion of Innovations (DOI) theory as the guiding framework. The DOI theory, first proposed by Everett Rogers in 1962, has been widely employed in educational research as a theoretical framework for studying the adoption of new educational technologies and practices (Menzli et al., 2022; Pinho et al., 2021). This decision is based on several key factors that make the DOI relevant and appropriate for the research context. First, the theory provides a comprehensive framework that encompasses critical attributes influencing the adoption of innovative technologies, such as relative advantage, compatibility, complexity, trialability, and observability (Rogers, 1987, 2003). These factors align with the researchers' aim to investigate AIAL among undergraduate students. Second, the research is conducted within the social system of a university in Hangzhou, where peer influence, instructor guidance, and the overall university environment play a significant role in shaping technology adoption decisions. The theory's emphasis on social context aligns with understanding how AIALs are adopted within this environment (Ganjipour & Edrisi, 2023). Third, the DOI theory recognizes the temporal aspect of adoption, acknowledging that adoption rates evolve. Given the dynamic nature of technology adoption, the research aims to capture the current state of AI technology adoption and provide insights into potential future trends among students. Lastly, the theory has proven efficacy in educational research, particularly in examining the adoption of novel educational technologies and practices (Menzli et al., 2022). This offers a strong foundation for the study, enabling the researchers to build upon prior research while tailoring their investigation to the unique context of AIAL in undergraduate education at a Chinese university in Hangzhou.

Scholars investigating the relationship between education and technology have emphasized its importance in the ongoing discussion about incorporating technology into education and its effects on learning. In the last decade, the adoption of Technology Enhanced Learning (TEL) in universities has significantly increased, in part due to government incentives and also to meet students' expectations. Researchers (e.g., Dunn & Kennedy, 2019) from different educational settings regularly use these factors to understand how technology is integrated, especially among students. The widespread recognition of these dimensions highlights their continued relevance in shaping education and providing valuable insights into how students adopt and use technology. These studies underscore the significance of these dimensions in comprehending the adoption of emerging technologies within different educational contexts. Table 1 showcases notable examples of scholars who have applied these dimensions in their research to gain insights into the relationship between education and emerging technologies. By building on this existing research and using the DOI framework, the researchers establish the theoretical foundation of this study and contribute to the ongoing discussion about technology adoption in education.

Table 1. Latent variables, their measurement, and relevant literature in AIAL among management students

Latent variables	Indicators used by other scholars	References	Relevance in this study
1. Intention to use	Factors influencing individuals' intention to adopt new technologies, including their attitudes and perceptions	(M. J. Alam et al., 2023; Al-Hattami, 2023; Gray et al., 2021; Kankam & Adinkrah, 2023; Lisana, 2023; Muflih et al., 2021; Y. Wang & Wu, 2023)	Study the factors that influence management students' intention to adopt AI innovations for the studies.
2. Relative advantage	Emphasizes the importance of the perceived relative advantage of innovated technologies compared to existing alternatives.	(Al-Hattami, 2023; Alyoussef, 2023; Cui et al., 2023; Lisana, 2023; Talebian et al., 2014)	Explore how management students perceive the benefits of AI in education over traditional methods.
3. Trialability: recognizes the …	Recognizes the significance of trialability in the adoption process of education.	(De Grove et al., 2012; Hamidi & Chavoshi, 2018; Mashroofa et al., 2023; Matsika & Zhou, 2021)	Investigating how the opportunity for management students to experiment with AI technologies affects their adoption intentions.
4. Complexity	Addresses the perceived complexity of new technologies.	(Alyoussef, 2023; Ganjipour & Edrisi, 2023; Mhlongo et al., 2023)	Assessing how management students perceive the complexity of AI technology and how it impacts their willingness to use it.

Latent variables	Indicators used by other scholars	References	Relevance in this study
5. Compatibility	Highlights the importance of compatibility with existing practices in education.	(Ganjipour & Edrisi, 2023; Mashroofa et al., 2023; Menzli et al., 2022)	Examine how AI technologies align with current educational practices and whether this compatibility influences adoption.
6. Observability	Acknowledges the role of observability, which refers to the visibility of the new technology's benefits for students.	(Ganjipour & Edrisi, 2023; Menzli et al., 2022; Pinho et al., 2021; Safari et al., 2022)	Observe the advantages of AI technologies in education and how this affects their adoption intentions.

The study utilizes the Diffusion of Innovations Theory (DOI) as a framework, supplemented by insights from existing literature, following established research practices. Researchers examine the implementation of AIAL in undergraduate management education, focusing on critical dimensions such as intention to use, relative advantage, trialability, complexity, compatibility, and observability. These dimensions are crucial factors in the adoption of technology in educational settings.

METHODOLOGY

The study analyzes the survey responses statistically to obtain quantifiable and generalizable insights on adopting the AIAL environment. The participants volunteered to participate, and the data collected was solely for research purposes to protect their privacy. Maintaining the anonymity of all participants was a top priority and a crucial ethical consideration in research (Roberts & Allen, 2015). Confidentiality and anonymity were upheld to ensure ethical standards were met and to enhance the study's integrity.

The study was conducted at Hangzhou universities due to its technological advancement and diverse student population, providing varied perspectives on AI adoption (Pillai et al., 2024). Among management students aged 18 to 21, 420 online self-administered questionnaires were randomly distributed, which included a brief description of the study objectives. The online survey offers several advantages, including efficient data collection from a large and diverse sample of students and ease of participation and data management (Chen et al., 2020; Steinberg, 1994). The online surveys are suitable for gaining various perspectives on integrating AI among undergraduate students (Granić, 2022a). Participants could respond to the questionnaire conveniently using their smartphones, tablets, or laptops. The questionnaire was divided into seven sections. The first section comprised demographic profiles of the respondents, such as gender and age. The second to seventh sections comprised of items that measured the respondents' perceptions of Intention to Use AI Technologies in Education (IUAITE), Perceived Relative Advantage of AI Technologies in Education (PRA), Trialability of AI Technologies in Education (TRIAITE), Perceived Complexity of AI Technologies in Education (COXAITE), Compatibility of AI Technologies in Education (COTAITE), and Observability of AI Technologies in Education (OBSAITE) respectively. Researchers applied a prior sample size estimation to calculate the minimum sample size required for this study to avoid type I and II errors (She et al., 2021). In our study, we initially calculated a minimum sample size of 382 participants based on an approximately 50,000 population, with a 95% confidence interval and a 5% margin of error. However, due to practical constraints, we could only collect 312 participants. Despite falling short of our target, we achieved a high response rate of 81.68%, which lends credibility to our findings. The dataset and the questionnaire can be accessed through the Adoption of AI in Education repository on Mendeley Data (https://doi.org/10.17632/hwpxz98swn.1). The details of the respondents' demographic profiles are shown in Table 2.

Table 2. Demographic characteristics of respondents

Category	Subcategory	Number	Percentage
Gender	Male	112	35.9%
Gender	Female	200	64.1%
Age	18	48	15.4%
Age	19	76	24.4%
Age	20	114	36.5%
Age	21	74	23.7%

The study utilized the partial least squares structural equation modeling (PLS-SEM) method with the SmartPLS version 4.0.9.6 for data analysis. This method is particularly advantageous for researchers as it allows for estimating complex models with numerous constructs, indicator variables, and structural paths without imposing distributional assumptions on the data (Hair et al., 2021b, 2022). PLS-SEM is a causal-predictive approach to SEM that prioritizes prediction in estimating statistical models designed to provide causal explanations. This technique bridges the gap between explanation and prediction, which forms the basis for developing managerial implications (Avkiran, 2018; Hair et al., 2021b).

DATA ANALYSIS AND RESULTS

The first step was to screen the data by examining each variable's frequencies and minimum and maximum scores. Addressing missing data is crucial, as it can result from various factors such as respondent unfamiliarity, data entry errors, or refusals to an answer (S. Alam et al., 2023). Missing data and outliers were also checked. There were no missing values or actual outliers. Researchers employed Harman's single-factor test, following the guidelines to detect common method bias (Podsakoff et al., 2003). All the variables were subjected to a principal component analysis, which yielded a six-factor solution with eigenvalues greater than one. The total variance explained was 68.73%, with the first component accounting for only 16.32%. The study is free from common method bias. While the data screening process reveals no missing values or outliers, further analysis uncovers underlying patterns and relationships within the dataset.

TEST FOR MULTIVARIATE ASSUMPTIONS

Researchers must test multivariate assumptions such as linearity, normality, and homoscedasticity before conducting multivariate analysis (Mustafa et al., 2022; Williams et al., 2013). In statistical analyses, assuming linearity when examining variable relationships is common. However, real-world data often exhibit non-linear patterns (Williams et al., 2013). Deviations in skewness or kurtosis from normality can affect analysis outcomes (Wulandari et al., 2021). This study's normality was not fully met, as indicated by the P-P plots in Figure 1.

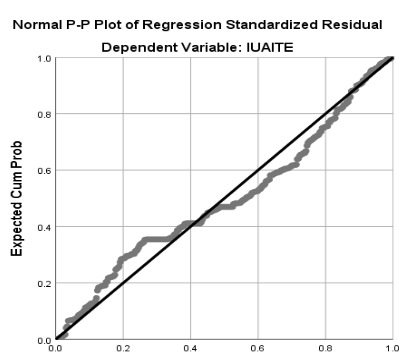

Figure 1. P-P plot

Table 3 presents the descriptive statistics, including skewness and kurtosis, for each variable examined in the study, providing insights into the distribution and variability of the data. Although this study did not fully meet the normality assumption, the analysis found homoscedasticity as the residuals were evenly distributed. Despite this issue, the study utilized PLS, which is a reliable method even when certain assumptions are not met (Hair et al., 2022; Ringle et al., 2010). P-P plots and descriptive statistics provide insights into the distribution of variables, guiding subsequent modeling decisions. There was no issue of multicollinearity among the variables.

Table 3. Descriptive statistics

	N	Skewness		Kurtosis	
Variable	Statistic	Statistic	Std. Error	Statistic	Std. Error
IUAITE	312	-.061	.138	-.519	.275
PRA	312	.279	.138	-.306	.275
TRIAITE	312	.153	.138	-.270	.275
COXAITE	312	.362	.138	-.056	.275
COTAITE	312	.148	.138	-.225	.275
OBSAITE	312	-.008	.138	-.029	.275
Valid N (listwise)	312				

Confirmatory Tetrad Analysis (CTA)

We used the CTA-PLS-SEM measurement model, and the method used Confirmatory Tetrad Analysis (CTA) aligned with partial least squares structural equation modeling (PLS-SEM) assumptions (Gudergan et al., 2008). Based on CTA analysis, IUAITE and COXAITE are formative models, and the results of the CTA are given in Table 4. The results in this table display the outcomes of the CTA, distinguishing between formative and reflective models for each construct under investigation. On the other hand, PRA, TRIAITE, COTAITE, and OBSAITE are reflective models. Therefore, the researchers used the Consistent PLS algorithm and Consistent PLS bootstrapping to evaluate the measurement and structural models following the literature (Hair et al., 2021b; Kapoor & Dwivedi, 2020).

Table 4. Confirmatory Tetrad Analysis (CTA)

Constructs (No of indicators)	CI Low Adj<0<CI-High Adj	Status
IUAITE	Yes	Formative
PRA	Yes	Reflective
TRIAITE	Yes	Reflective
COXAITE	No	Formative
COTAITE	Yes	Reflective
OBSAITE	Yes	Reflective

The results of CTA inform subsequent modeling decisions, guide the selection of appropriate analytical techniques, and ensure the validity of study findings.

Evaluation of Measurement Model

In order to ensure accurate results, the analysis was conducted in two stages. First, the measurement model was evaluated, followed by the structural model (Henseler et al., 2012). Researchers reviewed the outer loadings during the measurement model assessment and checked for internal consistency across all constructs.

For a model to fit well, it is generally recommended that the path loadings be above 0.70 (Henseler et al., 2012, 2015). However, in social science research, it is not uncommon to encounter lower outer loadings (i.e., below 0.70), especially when using new scales (Hair et al., 2021b; Hulland, 1999). Instead of immediately disregarding indicators with outer loadings under 0.70, researchers assessed how the removal affects the internal consistency reliability or convergent validity beyond the recommended threshold. Thus, indicators with outer loadings between 0.40 and 0.70 should only be excluded if they improve reliability or validity (Hair et al., 2021b). Figure 2 indicates that the outer loadings of certain items fall below the 0.7 but more significant than the 0.4 threshold.

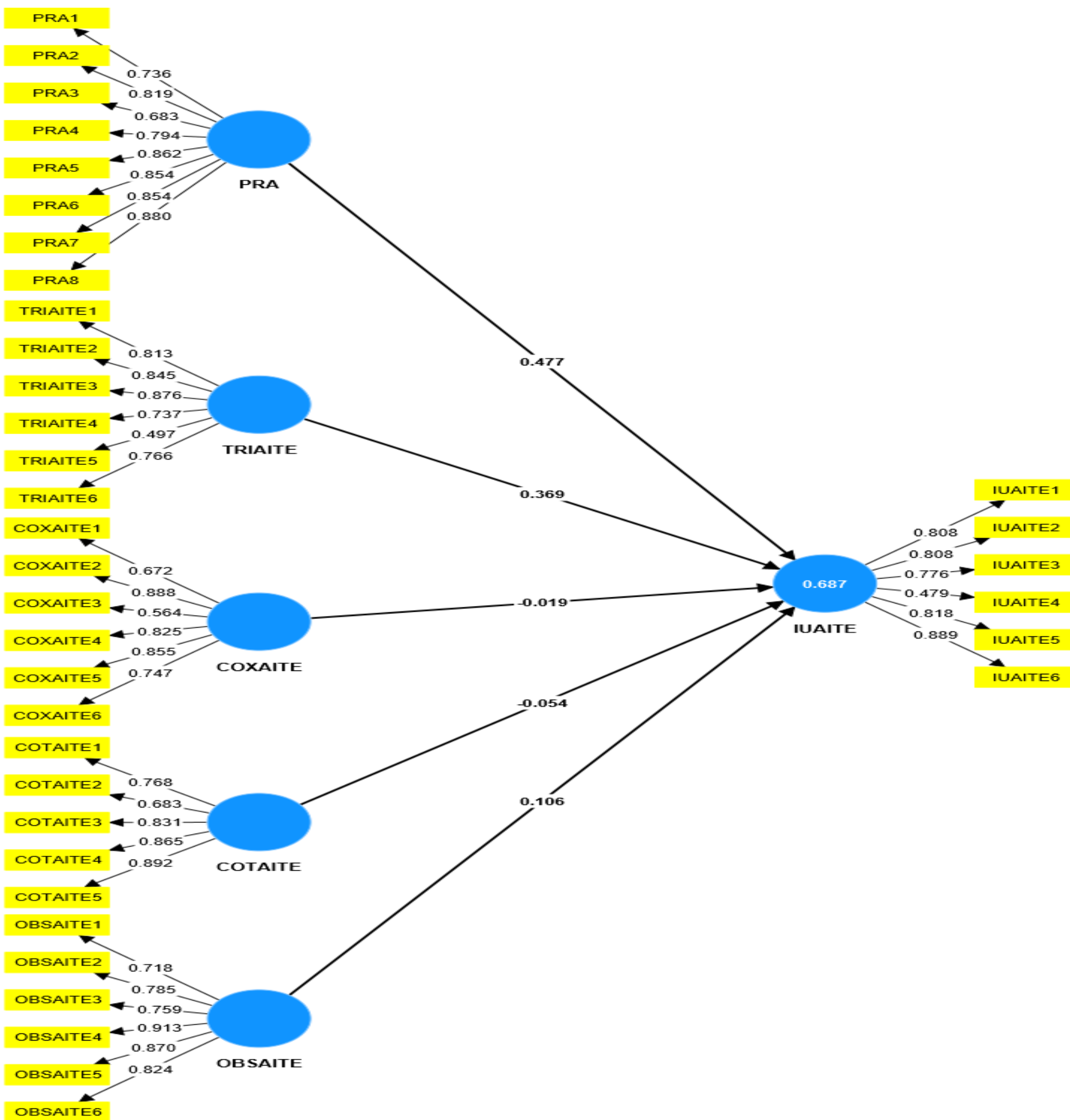

Figure 2. Indicators in the initial model

After examining each item individually against the requirement, it was determined that items IUAITE4 and TRIAITE5 should be excluded from the initial model. The final model depicted in Figure 3 confirms that all outer loadings of the items, except IUAITE4 and TRIAITE5, are above 0.5 and fall within the acceptable range.

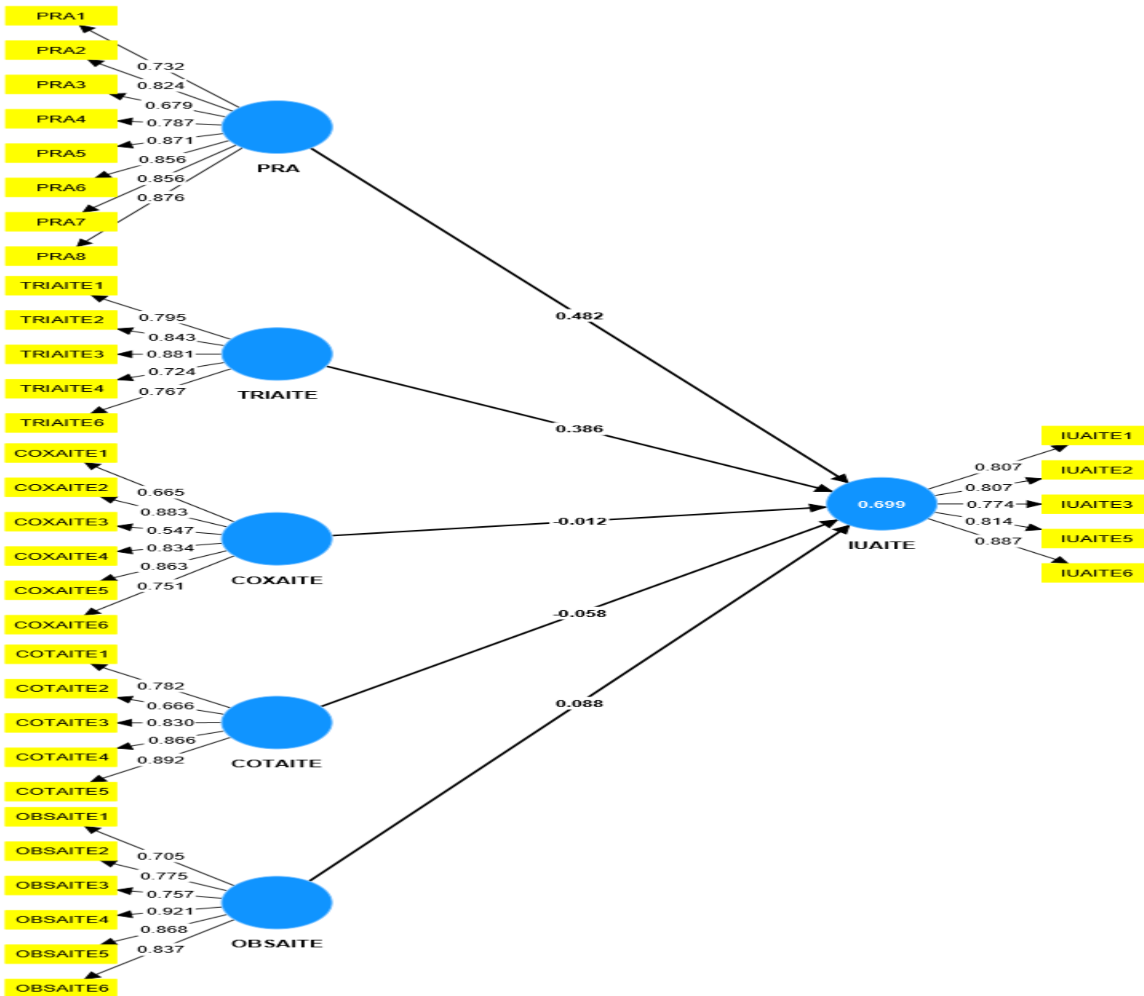

Figure 3. Indicators in the final model

The Cronbach alpha test is a commonly used tool for measuring internal consistency in research instruments. A low alpha score can be attributed to insufficient questions, weak item connections, or complex constructs (Tavakol & Dennick, 2011). In this study, all variables had alpha values above 0.80, indicating excellent reliability, as demonstrated in Table 5 (Sekaran & Bougie, 2016). Thus, Table 5 showcases the construct reliability and validity measures, including Cronbach's alpha, composite reliability, and average variance extracted (AVE), demonstrating the robustness and consistency of the measurement model.

Table 5. Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
COTAITE	0.905	0.912	0.905	0.658
COXAITE	0.894	0.907	0.893	0.588
IUAITE	0.911	0.912	0.910	0.671
OBSAITE	0.922	0.926	0.921	0.662
PRA	0.939	0.943	0.939	0.661
TRIAITE	0.900	0.904	0.901	0.646

In structural equation modeling (SEM), composite reliability (CR) is a measure used to assess the internal consistency or reliability of the latent constructs (factors) in a model (Hair et al., 2021a, 2021b). The researcher can confidently affirm the satisfactory convergent validity of the variables as per the findings in Table 5. The CR is higher than 0.7, and the AVE is greater than 0.5 and less than its corresponding (She et al., 2021).

The results in Table 6 show that all constructs have discriminant validity. Here, we apply the Fornell-Larcker criterion to assess discriminant validity among constructs, ensuring that each construct's variance exceeds its correlation with other constructs. This is demonstrated by the fact that the square root of AVE for each construct is greater than its correlation with other constructs, and all values of the Heterotrait-Monotrait ratio of correlations (HTMT) matrix, as shown in Table 7, are less than the recommended threshold of 0.85 (Henseler et al., 2015; Ringle et al., 2023). This table presents the HTMT matrix, evaluating the discriminant validity of constructs by comparing inter-construct correlations with intra-construct correlations.

Table 6. The Fornell–Larcker discriminant validity

	COTAITE	COXAITE	IUAITE	OBSAITE	PRA	TRIAITE
COTAITE	**0.811**					
COXAITE	0.605	**0.767**				
IUAITE	0.660	0.567	**0.819**			
OBSAITE	0.710	0.614	0.655	**0.814**		
PRA	0.758	0.589	0.799	0.687	**0.813**	
TRIAITE	0.771	0.716	0.782	0.736	0.798	**0.804**

Table 7. Heterotrait-Monotrait Ratio (HTMT)

	COTAITE	COXAITE	IUAITE	OBSAITE	PRA	TRIAITE
COTAITE						
COXAITE	0.606					
IUAITE	0.658	0.560				
OBSAITE	0.706	0.611	0.650			
PRA	0.758	0.583	0.797	0.684		
TRIAITE	0.777	0.711	0.781	0.740	0.801	

The correlation matrix reveals the relationships between the constructs examined in the study. Generally, moderate to strong positive correlations are observed among most pairs of constructs. Specifically, constructs such as COTAITE, COXAITE, IUAITE, OBSAITE, PRA, and TRIAITE exhibit correlations ranging from 0.560 to 0.801. These findings suggest significant associations between these constructs, indicating potential interdependencies or shared variance.

Existing Level of Variables

The results of the descriptive analysis indicate that Chinese students have a generally positive perception of AI technologies in education. This is reflected by the peak levels of various variables in Table 8, which score 5. The mean values of the variables are more significant than 3.66, indicating that there is a higher level of perceived intention to use AI technologies in education, perceived relative advantage of AI technologies in education, trialability of AI technologies in education, perceived complexity of AI technologies in education, compatibility of AI technologies in education, and observability of AI technologies in education among Chinese students.

Table 8. Descriptive statistics

	Minimum	Maximum	Mean	Std. Deviation
IUAITE	1.80	5.00	3.8865	.69269
PRA	2.00	5.00	3.7556	.65531
TRIAITE	2.00	5.00	3.8179	.61299
COXAITE	2.00	5.00	3.6725	.62035
COTAITE	2.00	5.00	3.7096	.64147
OBSAITE	1.50	5.00	3.7356	.68684

Descriptive statistics provided in this table offer insights into the distribution and central tendencies of variables, reflecting the perceptions of Chinese management students regarding the integration of AI technologies in education.

Assessment of Structural Model

After assessing the final measurement model, the proposed hypotheses were tested. When using PLS-SEM, it is essential to check for multicollinearity, which occurs when variables are interrelated and can affect reliability. After assessing the issue using the Variance Inflation Factor (VIF), researchers found no evidence of multicollinearity, as all VIF scores were below the accepted threshold of 5 (Akinwande et al., 2015).

The Standardized Root Mean Square Residual (SRMR) measures model fit by comparing observed and model-implied correlation matrices. The estimated model has SRMR values less than 0.08, confirming a good fit (Hu & Bentler, 1998). The R^2 value of 0.7 suggests that the independent variables explain 70% of the variability in perceptions related to the intention of using AI technologies in education. Based on this finding, the researcher can conclude that the model is satisfactory (Jacobsen et al., 2016). The F^2 statistic measures the amount of unexplained variance accounted for by the change in R^2 (Hair et al., 2021b). The analysis indicates that PRA significantly impacts IUAITE, with F^2 values greater than 0.15, signifying a 'medium' effect size. Additionally, TRIAITE exerts a minor effect on IUAITE, as indicated by F^2 values greater than 0.02. This demonstrates the varying magnitudes of influence between the predictor variables and IUAITE. Further, SRMR and R^2 values provide insights into model fit and explanatory power, respectively, supporting the structural model's overall validity. The redundancy coefficient, measuring the explanatory power of exogenous factors on a dependent factor's variance, impacts R^2 interpretation (Hair et al., 2021b, 2022). Q_2, or cross-validated redundancy, assesses predictive relevance; a Q_2 value of 0.592 was obtained in this study. The research concludes with a high degree of predictive relevance for the endogenous factor in the IUAITE model (Hair et al., 2021b, 2022).

The Structural Model and Hypotheses Testing

The analysis results in Figure 4 indicate that the relationships between COTAITE, COXAITE, and OBSAITE with IUAITE are not supported, as evidenced by non-significant T statistics, high p-values, and confidence intervals span zero. Conversely, the relationships of PRA and TRIAITE with IUAITE are supported, as indicated by significant T statistics, low p-values, and confidence intervals that do not include zero. These findings suggest that PRA and TRIAITE significantly impact IUAITE in the studied context.

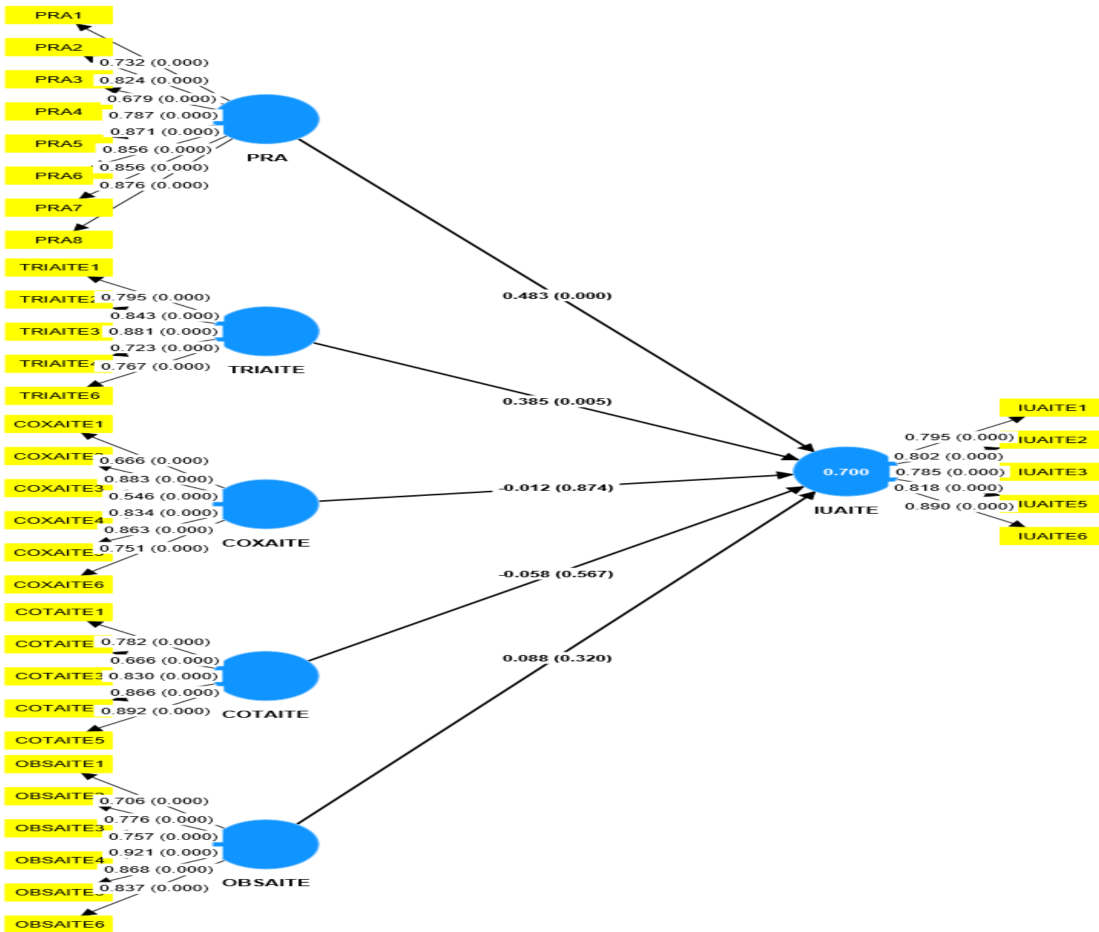

Figure 4. The structural model with path coefficients and P value

The direct effect path coefficients presented in Table 9 summarize the relationships between constructs in the structural model, indicating their significance and direction. The research's analysis and results provide valuable insights into the intricate perceptions of undergraduate students studying management in Hangzhou, China, regarding integrating artificial intelligence-assisted learning in education.

Table 9. Summary of direct effect path coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Confidence intervals		Decision
						2.5%	97.5%	
COTAITE -> IUAITE	-0.058	-0.067	0.102	0.573	0.567	-0.286	0.118	Not Supported
COXAITE -> IUAITE	-0.012	-0.014	0.075	0.158	0.874	-0.162	0.132	Not Supported
OBSAITE -> IUAITE	0.088	0.089	0.088	0.994	0.320	-0.091	0.258	Not Supported
PRA -> IUAITE	0.483	0.483	0.114	4.224	0.000	0.260	0.709	Supported
TRIAITE -> IUAITE	0.385	0.397	0.137	2.802	0.005	0.143	0.684	Supported

The following discussion section delves deeper into this multifaceted issue, examining how our findings align and deviate from existing literature. The researchers also explore the nuanced influences of cultural and contextual factors and provide a comprehensive understanding of the implications of AI adoption strategies in higher education.

DISCUSSION

The study provides valuable insights into the perceptions of management undergraduate students in Hangzhou, China, towards adopting Artificial Intelligence in their education. The findings reveal a high level of intention to use AIAL in education, with mean values of variables greater than 3.66. This indicates that management undergraduate students in Hangzhou, China, have a generally positive attitude towards integrating AI in educational settings. The researchers used the Diffusion of Innovations Theory (DOI) as the guiding framework that resonates with the broader educational technology literature. Numerous studies have successfully applied DOI to examine the adoption of innovative technologies in educational settings (Ganjipour & Edrisi, 2023; Pinho et al., 2021; Seo et al., 2021). As unveiled by the study, the robust intention to use AI technologies suggests a readiness and openness among management students in Hangzhou, China, to engage with cutting-edge technological advancements, paving the way for a potentially transformative educational experience. The findings contribute to a broader understanding of the evolving dynamics between students and technology in an educational context, particularly in AIAL in a region known for its technological prowess and academic excellence.

Although integrating AIAL in educational contexts has numerous benefits, one should also take into account the challenges associated with it (Baker, 2016). Rapid technological advancements bring several risks and challenges that have surpassed policy debates and regulatory frameworks. Some of these risks include data privacy and security threats, the possibility of AI producing inappropriate or incorrect results, and the potential for unwanted biases to be amplified (Rodway & Schepman, 2023). Thus, cautiously approaching AI technologies in education is essential to maintaining the core values of equity and inclusion in education (Holstein & Doroudi, 2021). By doing so, stakeholders can ensure that the ongoing technological revolution benefits everyone, especially in innovation and knowledge.

The significance of Perceived Relative Advantage (PRA) and Trialability (TRIAITE) in influencing AI technology adoption, as identified in this study, aligns with prior research (Al-Hattami, 2023; Alyoussef, 2023). The literature consistently emphasizes these factors as pivotal in adoption decisions. Perceived Relative Advantage (PRA) is the degree to which an innovation is perceived as better than the idea it supersedes (Almaiah et al., 2022). The higher the perceived relative advantage, the more likely the innovation will be adopted. This is supported by the findings of this study, where a significant favorable influence of PRA on the intention to use AI technologies in education was observed.

On the other hand, trialability refers to the degree to which an innovation may be experimented with on a limited basis (Almaiah et al., 2022). It is positively related to the likelihood of adoption. The concept of trialability is indeed a critical factor in adopting new technologies (Rogers, 2003). The ability to experiment with an innovation on a limited basis can significantly reduce uncertainty, decrease resistance, and facilitate adoption. This aligns with the results of this study, where an increase in TRIAITE corresponded with a rise in the intention to use AI technologies in education. In the context of AI technology adoption in education, these results suggest that students are more likely to adopt AI technologies if they perceive them as advantageous and have the opportunity to experiment with them before making a total commitment. This has important implications for how AI technologies are introduced and implemented in educational settings. If students perceive AI technologies as beneficial and capable of enhancing their learning experience, they are more likely to adopt them. Therefore, it is crucial to communicate the benefits of AI technologies effectively to students.

However, the study challenges some existing literature by indicating non-significant impacts of compatibility, complexity, and observability on the intention to use AI technologies in education (Khan & Qudrat-Ullah, 2021; Scott et al., 2008). Findings suggest that Compatibility (COTAITE), Complexity (COXAITE), and Observability (OBSAITE) did not exhibit a significant impact on the intention to use AI technologies. This contrasts with some literature that emphasizes the importance of these factors (Ganjipour & Edrisi, 2023; Mashroofa et al., 2023). The nuanced nature of technology adoption in educational settings may contribute to these variations. This divergence from established trends warrants further investigation and may be attributed to social and cultural contexts and influences, particularly in the Chinese context. The literature suggests that perceptions of technology can vary significantly across cultures and regions (Pillai et al., 2024). The study emphasizes the influence of socio-cultural factors on technology adoption, emphasizing the need for cross-cultural examinations in the literature. Perceptions of technology can vary significantly across cultures and regions, as observed in the nuanced nature of AI technology adoption among Chinese management students in Hangzhou. Hence, findings may not be universally applicable. Further, incorporating the temporal aspect of adoption, recognizing that adoption rates evolve, aligns with the dynamic nature of technology adoption. This aligns with the viewpoint that technology adoption is an ongoing process subject to change over time (Rogers, 1987).

Acknowledging the social context within a university environment reflects a well-founded understanding of technology adoption dynamics. Peer influence, instructor guidance, and the overall university environment have been recognized as influential factors in adopting student technology (Ganjipour & Edrisi, 2023). Peers play a significant role in shaping an individual's attitudes and behaviors, including their technology adoption. The interactions and shared experiences among peers can lead to the diffusion of positive or negative attitudes toward a particular technology (Granić, 2022a; McConnell et al., 2020; Miah et al., 2023). For instance, if a peer shares a positive experience with a specific technology, it may influence others in the group to adopt it. Instructors also play a crucial role in the adoption of technology. Their attitudes towards technology, proficiency in using it, and willingness to assist students in learning to use it can significantly influence students' adoption decisions (Lu et al., 2023; McConnell et al., 2020; Miah et al., 2023). Instructors can act as role models, demonstrating the benefits of technology and providing support and guidance to students as they learn to use it (Granić, 2022b; Lu et al., 2023). The university environment, including its culture, infrastructure, and policies, can also impact technology adoption. A supportive environment that encourages innovation and provides the necessary resources and infrastructure can facilitate technology adoption (Granić, 2022a; Miah et al., 2023). Conversely, an environment resistant to change or a lack of the necessary resources can hinder technology adoption (Hanaysha et al., 2023). Thus, peer influence, instructor guidance, and the overall university environment are interconnected and can collectively shape students' attitudes toward technology adoption. Understanding these dynamics can help develop strategies to promote technology adoption in educational settings.

While our study contributes valuable insights into AI technology adoption among Chinese management students, the cultural and contextual factors influencing adoption may differ in other global settings. This raises questions about the generalizability of findings and emphasizes the need for cross-cultural examinations in the literature. The study needed to fully meet the normality assumption, which might be a limitation. However, this resonates with the broader discourse in social sciences, acknowledging that normality assumptions are not always fully met and may not be critical for specific analyses (Hair et al., 2021b; Sarstedt et al., 2014). The literature suggests that perceptions of technology can vary significantly across cultures and regions (Pillai et al., 2024). Hence, findings may not be universally applicable. While our study needed to fully meet the normality assumption, this aligns with the broader discourse in social sciences, challenging the rigid adherence to statistical assumptions. Similarly, the generally positive perceptions of Chinese students towards AI adoption may be specific to the socio-cultural context of Hangzhou, highlighting the limitation of generalizability across diverse cultural settings.

Our study supports established theories and findings on technology adoption but also reveals the complex nature of this process, as evidenced by the varied impact of different factors. Our divergence from some existing literature highlights the importance of considering the context and the evolving nature of educational technology landscapes. Recognizing these variations contributes to a deeper understanding of technology adoption, which can help educators and policy makers tailor interventions that address the unique dynamics of AI integration in education. The study confirms existing literature and provides a more comprehensive view of AI technology adoption dynamics by considering differences and diversities. Future research could further explore the cultural influences on technology adoption, particularly in the Chinese context. Additionally, the non-significant impacts of compatibility, complexity, and observability identified in this study suggest potential areas for further investigation. Future studies could also consider other potential influencing factors not covered in this study, such as individual attitudes toward technology, prior experience with AI technologies, and the influence of peers and teachers.

CONCLUSION

The study examines how management undergraduates in Hangzhou, China, perceive the integration of AI-assisted learning in their education. The findings highlight a favorable intention among students to embrace AI technologies, with a prevalent positive attitude toward AI integration in educational settings. The study, guided by the Diffusion of Innovations Theory (DOI), contributes valuable insights to the broader educational technology literature. Notably, it highlights the influential roles of Perceived Relative Advantage (PRA) and Trialability (TRIAITE) in AI adoption, aligning with established research. These factors, reflecting AI's perceived superiority over traditional methods and the opportunity for experimentation, significantly impacted students' intention to use AI technologies.

Interestingly, the study challenges prevailing literature by highlighting the non-significant impacts of Compatibility (COTAITE), Complexity (COXAITE), and Observability (OBSAITE) on AI adoption intention. These deviations suggest a multifaceted technology adoption landscape influenced by social and cultural contexts, particularly in the Chinese educational setting. Such insights prompt further investigation into the dynamic nature of technology adoption and its evolution over time. The study acknowledges the influential roles of peers and instructors in shaping technology adoption. Peer interactions, shared experiences, and instructor guidance contribute significantly to students' attitudes and decisions regarding AI technologies. The university environment, encompassing its culture, infrastructure, and policies, also emerged as a critical factor influencing technology adoption among students. While the study provides a better view of AI adoption dynamics, emphasizing the variations and diversities in technology perceptions, it recognizes the need for cautious generalization. The positive attitudes observed among Chinese management students may be specific to the socio-cultural context of Hangzhou, urging future cross-cultural examinations.

These results provide significant insights for incorporating AI technologies in higher education. Identifying key factors, such as the Perceived Relative Advantage and Trialability, emphasizes the need to highlight the advantages and provide opportunities for trial use of AI technologies in educational contexts. Moreover, the non-significant effects of elements like Compatibility, Complexity, and Observability necessitate a detailed understanding of the social and cultural contexts that drive technology adoption dynamics. These findings can inform the creation of customized strategies and policies designed to foster the effective adoption and use of AI technologies across various educational settings. Moreover, the insignificant effects of some factors present opportunities to investigate further into potential determinants not examined in this study. In essence, this research contributes not only to the existing theories and findings on technology adoption but also unravels the nuanced nature of this process within the evolving landscape of educational technology. By acknowledging and understanding these variations, educators and policy makers can tailor interventions that resonate with the unique dynamics of AI integration in education, thereby fostering a transformative and culturally sensitive educational experience.

Limitations and Future Directions

This research provides valuable insights into AI integration in education, particularly among undergraduate management students. However, acknowledging the study's limitations is essential for comprehensively understanding the findings. The study was conducted exclusively among management undergraduate students in Hangzhou, China, which could limit the applicability of the findings to other academic disciplines or geographical regions due to unique cultural and contextual factors. The study's cross-sectional design provides a snapshot of students' perceptions at a specific time. A longitudinal approach in future studies could better understand how these perceptions adapt to changing technological landscapes. While the study explores the influence of peers and instructors on AI adoption, it does not delve into the specific mechanisms of these influences.

Further, future studies could conduct comparative research across different academic disciplines and regions to enhance our understanding of the cultural and contextual factors influencing AI adoption. This would contribute to a more nuanced understanding of the global dynamics of technology adoption. Future studies could also use qualitative methodologies, such as interviews or focus groups, to investigate how peers and instructors influence AI adoption. Understanding the specific roles, behaviors, and communication strategies that shape students' perceptions would enrich the current literature on the social dynamics of technology adoption. Given the non-significant impacts of certain factors in this study, further investigation into the nuanced interplay between compatibility, complexity, and observation with AI adoption intention is warranted. Exploring potential moderating factors or contextual influences that might alter the significance of these relationships would contribute to a more comprehensive understanding of the factors influencing AI adoption.

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AUTHORS

Dr. Qiubo Huang received his Ph.D. in Business Administration from Zhejiang Gongshang University, China, and is an associate professor of Service Innovation and Management at Zhejiang Shuren University School of Economics and Social Welfare. His research focuses on service innovation and management related to industry servitization and digitalization. In addition to holding academic posts, he is working with a multidisciplinary team to design a course on innovation and marketing management in the modern service industry. He has participated in or led several public and private organizations in the field of online health management and services in China, including Zhejiang key research base of Philosophy and Social Sciences (Zhejiang Modern Service Industry Research Center), which is a university-based institute that engaged in outreach, consultation, and training for field of service

economy and management. E-mail: qiubo_huang@zjsru.edu.cn, Tel: 13588391521, ID-Number: 330421198109195718, ORCID: 0000-0002-2169-85623. Affiliation: School of Economics and Social Welfare, Zhejiang Shuren University, Hangzhou, Zhejiang, China, 310015. Detailed Address: Shuren Street, Gongshu District, Hangzhou, Zhejiang, China.

Prof. Pivithuru Janak Kumarasinghe is a professor at the Faculty of Management Studies at the University of Sri Jayewardenepura. He has authored several articles on the subjects of development economics and entrepreneurialism. He is currently a visiting professor in the College of Economics and Livelihood and Welfare at Zhejiang Shuren University, located at 8 Shuren Street in Hangzhou, Zhejiang Province, China. In addition to his academic roles, he collaborates with a diverse team of experts to develop a course on business economics. He also enriches the academic community by delivering guest lectures at various state universities in Sri Lanka and abroad. His expertise extends to providing consultancy services for both public and private sectors, focusing on entrepreneurship and business development. E-mail: janak_kumarasighe@zjsru.edu.cn, Mobile: 008618868433749, ORCID: 0000-0002-6223-1168

Mrs. Gothami Sakunthala Jayarathna is a visiting lecturer affiliated with the Faculty of Management at the Horizon Campus, The National Institute of Business Management (NIBM), and the Institute of Graphics Designing and Printing (INGRIN), Sri Lanka. She obtained her bachelor's degree from the University of Sri Jayewardenepura and pursued her master's studies at the Faculty of Graduate Studies at the same university. Previously, she worked as a Computer Instructor in the Information Technology Resource Center at the University of Sri Jayewardenepura. She provides research consultation in Economics, Business Statistics, Project Management, Finance, and Information Technology. Contact details: Tel: +94753105003 and +94715104069, ORCID: 0000-0001-9146-713X. E-mail address: gothami.usjp@gmail.com.