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Research Article

AI-Driven Strategies in Strategic Communication: Understanding University Students' Attitudes

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ABSTRACT

Introduction: Artificial intelligence (AI) is rapidly reshaping higher education, making it essential to understand students' acceptance of AI-based learning tools. This study extends the Technology Acceptance Model by incorporating AI Familiarity, Self-Efficacy, Perceived Personalization, Institutional Support, and Ethical Concerns. Using survey data from 473 students at Hebei Academy of Fine Arts and Structural Equation Modeling, the research tests eight hypothesized relationships. The goal is to clarify how AI-related factors influence Perceived Usefulness, Perceived Ease of Use, and students' attitudes toward AI adoption.

Objectives: This study examines university students' acceptance of AI-based learning tools by extending the Technology Acceptance Model (TAM) with additional constructs relevant to AI use in education, including AI Familiarity, Self-Efficacy, Perceived Personalization, Institutional Support, and Perceived Ethical Concerns.

Methods: A cross-sectional quantitative survey was conducted with 473 students from Hebei Academy of Fine Arts in China. Structural Equation Modeling (SEM) was employed to assess the measurement and structural models, evaluate construct validity, and test eight hypothesized relationships within the extended TAM framework.

Results: Seven of the eight hypotheses were supported. AI Familiarity and Self-Efficacy significantly increased Perceived Ease of Use, while Perceived Personalization and Institutional Support positively influenced Perceived Usefulness. Perceived Usefulness and Perceived Ease of Use strongly predicted students' attitudes toward AI adoption. Perceived Ethical Concerns did not significantly affect attitudes. The model demonstrated strong explanatory power, with ATT (R^2 = 0.768) being the most strongly predicted construct.

Conclusions: Findings show that AI Familiarity and Self-Efficacy improve Perceived Ease of Use, while Personalization and Institutional Support enhance Perceived Usefulness; Ethical Concerns show no significant effect. Perceived Usefulness and Perceived Ease of Use remain key predictors of attitudes, and the model demonstrates strong explanatory power (R^2 = 0.768). Although limited by a single-institution sample and self-reported data, the study highlights directions for broader future research. Overall, it enriches TAM literature in the AI education context and offers practical guidance for fostering supportive and responsible AI-enhanced learning environments.

Keywords: AI adoption in education; extended technology acceptance model; student attitudes toward ai; institutional support and ethics; personalization in learning technologies

INTRODUCTION

Artificial Intelligence (AI) has rapidly transformed multiple sectors, and education is one of the most profoundly affected fields. AI technologies have introduced new possibilities for pedagogy, curriculum development, assessment, and student interaction, prompting calls for their systematic integration into educational systems to support future digitalised societies. Scholars argue that AI in education must align with broader goals of sustainable and responsible development in the era of Industry 4.0 (Abulibdeh et al., 2024).

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In higher education, generative AI tools such as ChatGPT have reshaped learning by enabling personalised feedback, adaptive guidance, and interactive learning experiences. However, their adoption has also raised institutional concerns regarding academic integrity, plagiarism, privacy, and governance (Appleby, 2023; Farhi et al., 2023). These tensions reflect the dual narrative surrounding AI in education—optimism about its pedagogical affordances and caution toward its ethical and regulatory implications.

Despite ongoing curriculum reforms aimed at integrating AI knowledge and digital literacy (Chiu, 2021; Chiu et al., 2022), significant challenges persist. Research highlights disparities in students' familiarity, self-efficacy, and readiness to use AI tools, alongside concerns related to data use, fairness, and over-reliance on automated systems (Chiu et al., 2023; Gonzalez-Calatayud et al., 2021). Together, these issues emphasize the need for evidence-based approaches that balance innovation with responsible implementation.

The aim of this study is to examine university students' acceptance of AI-based learning tools by employing the Technology Acceptance Model (TAM) and extending it with contextually relevant constructs, including AI Familiarity, Self-efficacy, Perceived Personalization, Institutional Support, and Ethical Concerns. By analysing the relationships among these factors, this study seeks to identify key determinants of student attitudes toward AI adoption and offer insights to guide curriculum design and educational policy for ethical and effective AI integration in higher education.

OBJECTIVES

Haleem, Javaid, and Singh (2022) brought about ChatGPT as an important future assistance tool, describing its characteristics, capabilities, and limitations. Their consideration highlighted ChatGPT's potential for improving efficiency in research and education but also questioned the spread of misinformation, hallucinations, and overdependence, placing the technology as both revolutionary and challenging. Likewise, Holmes et al. (2021), using a UNESCO policy guidance, investigated the educational role of AI with specific considerations regarding inclusivity, governance, and the sustainable implementation of policies. Their study presented a global approach, calling on policymakers to enact responsible measures for embracing AI without exacerbating digital divides.

Ethical aspects were the core consideration in the following research. Huallpa (2023) investigated ChatGPT ethical issues in higher education, citing plagiarism, authorship uncertainty, and the erosion of academic integrity as immediate challenges. Likewise, Karaca et al. (2021) designed and tested the AI readiness Scale for medical students and noted the necessity to equip upcoming professionals with technical skills and ethical sensitivity. Kooli (2023) critically reflected on chatbots in education and research, identifying ethical concerns including bias, fairness, and privacy threats, against the backdrop of proposing regulation protection.

Systematic reviews have synthesized such debates. Lo (2023) carried out a survey in gen AI used in education and concluded that it enhances the efficiency of learning but still triggers concerns about accuracy, accountability, and academic abuse. Ou et.al., (2023) conducted a survey among Swedish university students and ascertained that although the majority viewed chatbots as helpful in learning, the issues of reliability and excessive dependence remained. Substantiating this, Nam (2023) outlined that 56% of American college students had already utilized AI in homework or test tasks, illustrating the mainstreaming of generative AI within student practice.

Certain uses of AI were also comprehensively researched. Nigam et al. (2021) undertook a survey of AI-proctoring systems, reporting gains in efficiency with concerns of surveillance and ethical unease on the part of students. Nori et al. (2023) tested whether generalist foundation courses like ChatGPT could perform better than specialized models in medicine, with implications of uncertainty about precision and reliability in high-stakes situations. A related study by Okulich- Kazarin et al. (2024) assessed whether students believed AI could replace teachers, revealing that while students recognized AI's efficiency, they resisted the idea of replacing human educators.

In addition, developments in concepts have influenced the discourse. Jiao at.al., (2021) proposed three education standards of AI (tutee, tool, and tutor) as a framework to conceptualize the protagonist of AI technologies in different learning scenarios. Papadopoulos et al. (2020) provides a survey on assistive robots in pre-tertiary education which indicates the potential for higher levels of engagement, but also raises issues around cost and access. Rahman et.al., (2023) wrote about ChatGPT for learning and research, and said while it could be personalised it could also be

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dangerous for academic abuse. Rodway et.al., (2023) estimated the effect of AI on development fulfilment in the higher education sector and found that students were grateful for the level of productivity AI tools were able to generate, but were still unsure on how to regulate it.

Education for the health care profession has long been a topic for research. Sallam (2023) has reviewed the use of ChatGPT in health departments and concluded that it is promising but there are justifiable concerns regarding misinformation and ethics as it relates to safety. Singh et.al., (2023) surveyed students in computer science on their attitudes toward ChatGPT and found mostly positive views around efficiency, but high levels of concern for student and academic risks in ethics.

More general patterns of adoption are identified by Smith and Jones (2019), who compared AI adoption by region, finding differences according to institutional readiness and cultural contexts. Von Garrel and Mayer (2023) found that German students do indeed widely use ChatGPT, but expressed worry about over-reliance on it. Williamson and Eynon (2020) gave a historical account of AI in education, pointing out a lack of theoretical connections between pedagogy and technology. Lastly, Zhu et al.(2023) talked of how to utilize ChatGPT efficiently, emphasizing the development of governance frameworks ensuring accountability, openness, and educational impact.

Notwithstanding this emerging body of research, there are still some limitations. First, most studies are exploratory and do not have longitudinal analysis, hence it becomes hard to evaluate the long-term effects of AI adoption on learning outcomes. Second, much of the existing literATTre is overly focused in Western environments, especially Europe and North America, leaving a shortfall in views from the developing world where adoption issues might be very different. Third, ethical issues are well-documented, but the majority of research uses student self-report surveys and not experimental or longitudinal designs that might confirm assertions more substantively. Fourth, discipline-specific research, particularly in medical school and proctoring schemes, is disconnected, inhibiting generalization between fields. Finally, sustainability issues in tertiary education are more recent and uncharted and need further empirical testing to learn about institutional resilience in an age of AI.

The Technology Acceptance Model (TAM), introduced by Davis (1989), stands as one of the most influential and parsimonious theories for predicting and explaining an individual's acceptance and adoption of information technology. Its core strength lies in its ability to identify the fundamental drivers of technology usage behavior through a limited set of causal relationships.

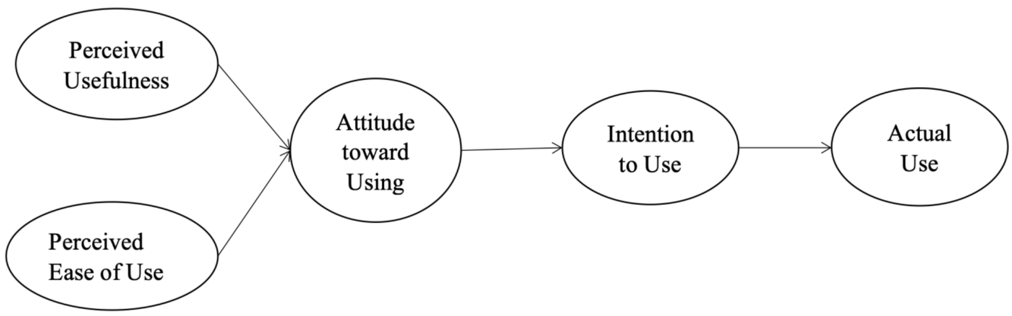

Figure 1- Technology Acceptance Model (TAM)

The original TAM posits that two primary belief constructs Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are the principal determinants of a user's Attitude Toward Using (ATT) a technology. This attitude, in turn, shapes the user's Behavioral Intention (BI) to use it, which is the most direct antecedent of Actual Use behavior. Specifically, Perceived Usefulness (PU) is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). In an educational context, this translates to the degree to which a student believes that using an AI technology will improve their learning performance, grades, or productivity. Perceived Ease of Use (PEU) is defined as "the degree to which a person believes that using a

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particular system would be free from effort" (Davis, 1989, p. 320). It refers to the user's perception that learning to interact with and operate the AI tool will be straightforward and unintimidating.

A critical relationship within TAM is the influence of PEU on PU; a technology that is easier to use is often perceived as more useful because less effort is required to achieve benefits (Davis, 1985). For decades, TAM's robust and simple framework has proven highly generalizable across a vast array of technologies and user populations, making it an ideal foundational theory for this study.

While the Technology Acceptance Model (TAM) provides a robust and parsimonious foundation for understanding technology adoption, its core constructs of Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are often insufficient to fully capture the complexity of adoption behaviors in specific, novel contexts (Venkatesh & Bala, 2008). The application of Artificial Intelligence (AI) in education presents a unique scenario characterized by its perceived personalization capabilities, significant ethical implications, and a dependency on both individual competencies and institutional infrastructure. Therefore, to develop a more comprehensive and context-sensitive research model, this study extends the original TAM by integrating five key external variables: AI Familiarity, Self-Efficacy, Perceived Personalization, Institutional Support, and Perceived Ethical Concerns.

Drawing from the Diffusion of Innovations (DOI) theory (García-Avilés, 2020), familiarity reduces the uncertainty and complexity associated with a new technology. AI Familiarity is crucial as AI is still an emerging technology for many students; their prior exposure directly impacts initial perceptions of ease. The definition of AI Familiarity is the degree to which an individual has prior exposure to, knowledge of, and experience with artificial intelligence concepts and technologies (Schulenberg & Melton, 2008). Students with higher AI familiarity are likely to find AI-based learning tools less intimidating and more straightforward to interact with. Therefore, it is hypothesized that AI Familiarity will positively influence Perceived Ease of Use (PEU).

H1: AI Familiarity (AIF) will positively influence Perceived Ease of Use (PEU).

Rooted in Bandura's (1986) Social Cognitive Theory, self-efficacy is a powerful predictor of behavior. Self-Efficacy is paramount because using AI effectively often requires a willingness to engage with complex and sometimes unpredictable systems. An individual's judgment of their capability to organize and execute the courses of action required to accomplish specific tasks (Compeau & Higgins, 1995). Students with high computer self-efficacy are more confident in their ability to overcome challenges when using new technology. This confidence directly reduces the perceived effort required, leading to the hypothesis that Self-Efficacy will positively influence Perceived Ease of Use (PEU).

H2: Self-Efficacy (SE) will positively influence Perceived Ease of Use (PEU)

Personalization is a key value proposition of AI. Perceived Personalization taps into the core pedagogical promise of AI, which is to deliver customized learning experiences. The extent to which a user believes that an AI-driven system can tailor its content, interactions, and recommendations to their individual preferences, needs, and learning styles (Shanahan et al., 2018; Sherrie & Benbasat, 2006). When students perceive that an AI tool understands and adapts to their unique needs, they are more likely to believe it will be effective in enhancing their learning outcomes. Thus, it is hypothesized that Perceived Personalization will positively influence Perceived Usefulness (PU).

H3: Perceived Personalization (PP) will positively influence Perceived Usefulness (PU).

Strong institutional support mitigates potential barriers (e.g., lack of know-how, access issues) and signals the tool's importance and reliability, thereby enhancing its perceived utility. Institutional Support recognizes that the adoption of advanced educational technology is not solely an individual choice but is facilitated or hindered by the learning environment. The degree to which a student believes that their educational institution provides adequate resources, training, guidance, and technical infrastructure to facilitate the use of AI technologies (Kazumi & Kawai, 2017). Therefore, it is hypothesized that Institutional Support will positively influence Perceived Usefulness (PU).

H4:Institutional Support (IS) will positively influence Perceived Usefulness (PU).

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Based on the core theoretical framework of the Technology Acceptance Model (TAM), this study posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEU) collectively form the key cognitive foundations shaping students' Attitude Toward Using (ATT) AI technologies in classroom learning.

Specifically, when students believe that AI technologies can effectively enhance their learning performance and efficiency (i.e., a high level of PU), and when using these technologies requires minimal effort (i.e., a high level of PEU), they are more likely to develop a positive attitude toward their use. At the same time, Perceived Ease of Use also significantly influences Perceived Usefulness AI tools that are easy to operate better demonstrate their functional value, thereby strengthening students' perception of usefulness.

Thus, this study proposes the following hypotheses:

H5: Perceived Ease of Use (PEU) has a significant positive influence on Perceived Usefulness (PU).

H6: Perceived Usefulness (PU) has a significant positive influence on Attitude Toward Using (ATT).

H7: Perceived Ease of Use (PEU) has a significant positive influence on Attitude Toward Using (ATT).

Research on technology acceptance increasingly highlights the role of trust and risk. Perceived Ethical Concerns acknowledges the prevalent societal and personal anxieties regarding data privacy, algorithmic bias, and transparency, which are particularly acute in a learning context involving personal data. Ethical concerns can create significant psychological barriers and negative affective responses, which can negatively impact one's overall evaluation of the technology. Consequently, it is hypothesized that Perceived Ethical Concerns will negatively influence Attitude Toward Using (ATT) AI.

H8: Perceived Ethical Concerns (PEC) will negatively influence Attitude Toward Using (ATT) AI.

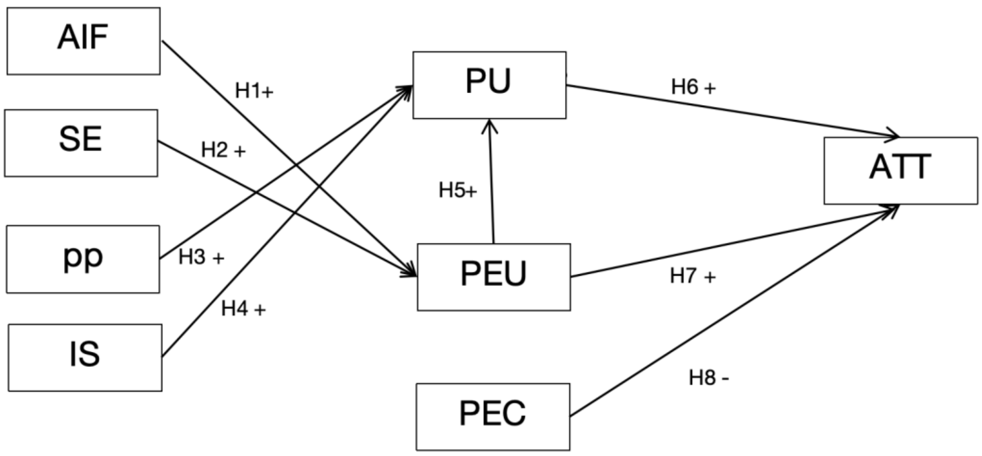

Figure 2- Conceptual Framework

METHODS

Research Design

This research used a cross-sectional, quantitative survey design based on the framework of the TAM. The target population of this study consists of university students from Hebei Academy of Fine Arts in Shijiazhuang, Hebei Province, China. Compared to internationally prevalent AI tools such as ChatGPT, the most widely used AI applications in China include DeepSeek, Doubao, and ChatGPT. Therefore, in the context of this survey, the term "AI software" specifically refers to DeepSeek, Doubao, and ChatGPT. Classical TAM constructs; PU, PEU and ATT were also combined with other variables like AIF, SE, IS, PEC, and PP. The multidimensionality of using AI-based tools like DeepSeek, Doubao and ChatGPT by students is manifested in the combination of such constructs. SEM was selected as it is possible to test both measurement and structural models simultaneously and estimate the degree of validity and reliability, as well as the inter-variable relationships. SEM can be formally represented as by Eq.1,

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$$\eta = B\eta + \Gamma \xi + \zeta \quad (1)$$

In this case, η refers to endogenous latent constructs, ξ is exogenous latent constructs, B shows the coefficient of relation between the endogenous variables, Γ is the regression weight of the exogenous variables on the endogenous variables, and ζ is the error. The rationale behind the selection of this research design is due to the fact that the theory-driven framework enables us to conduct rigorous hypothesis testing, as well as enables us to empirically test the relationships between the constructs in order to establish their causal relationships, not to mention the fact that this type of research design also enables us to factor in the measurement error.

Population and Sampling

The research population comprised postgraduate and undergraduate students of any discipline of Hebei Academy of Fine Art (HAFA), which located in Shijiazhuang city, Hebei province, China. The population of HAFA is 31,000. In order to identify the minimum sample size necessary to ensure a sufficient level of statistical power to explain the relationships in the model, this study follows Yamane's (1967) formula for sample size determination. Based on this calculation, the minimum required sample size is approximately 395 respondents. However, a larger sample size may be considered to account for potential non-response bias and incomplete responses and enhance the generalizability of the findings.

The sampling strategy was purposive; that is, the respondents who were familiar with AI or were pursuing disciplines with digital exposure were used. 473 valid responses were achieved exceeding the number of responses needed to qualify as SEM. Demographic information showed that 67.86 were female and 32.14 were male with the overwhelming percentage of 98.73 being undergraduates. The sample size confirmed that the sample was mainly composed of younger individuals as most of the participants were under the age of 24 (99.37%). The student distribution of the academia was as follows Computer Science/IT students (63.42), Social Sciences (17.34), Communication/Film (7.4), and other subjects (11.84). The experience of using AI was extensive with 88.79% indicating a prior usage of AI tools.

Inadequacy of the sample was also justified by statistical requirements. As per the rule of thumb of SEM, $N > 10 \times$ "number of items". Having 32 observed items, not less than 320 participants were required. This threshold was met in the last dataset (473) giving sufficient statistical power. This also guaranteed the sample to be representative of digitally literate and young students and hence the results were statistically sound as well as contextually applicable in a higher educational context.

Instrumentation

The instrument consisted of a structured questionnaire adapted from validated TAM and AI acceptance scales. Each construct was measured with multiple indicators using a five-point Likert scale. PU was measured by four items, PEU by three items, SE by two items, and other constructs similarly. The psychometric properties of the instrument were verified through internal consistency and validity testing. Internal reliability was assessed using Cronbach's alpha was given in Eq.3,

$$\alpha = (k / (k - 1)) \times (1 - (\Sigma\sigma_i^2 / \sigma_t^2)) \quad (2)$$

where k is the number of items, σ_i^2 the variance of each item, and σ_t^2 the total variance of the construct. All constructs were above the 0.82 threshold and thus, proved to be highly reliable. CR was computed for overall construct reliability and was defined in Eq.4.

$$CR = ((\Sigma\lambda_i)^2) / ((\Sigma\lambda_i)^2 + \Sigma\theta_i) \quad (3)$$

where λ i are factor loadings and ο i the errors. All constructs had CR values that were above 0.88. Convergent validity was evaluated on the basis of AVE presented in Eq.5,

$$AVE = (\Sigma\lambda_i^2) / (\Sigma\lambda_i^2 + \Sigma\theta_i) \quad (4)$$

with all constructs achieving AVE > 0.70. This established the robustness of the instrument for subsequent CFA and SEM analyses.

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Data Collection

The data were collected through online surveys distributed by China's popular social media wechat. The objective of the study and the right of the respondents to partake in the study was communicated to them. Informed consent was taken at the start of the survey and confidentiality guaranteed. Only responses that were filled in were retained to then be analysed resulting in a clean dataset of 473 cases. The AI knowledge was screened as balanced with 45.67 per cent saying yes, 41.23 per cent saying a little and 13.11 per cent saying no.

Methodological rigor was provided in the process by various checks. First, testing of responses was carried out with regard to missing data and anomalies. Second, the normality of the dataset was analysed and skewed. This guaranteed research ethics compliance with the quality of data. The data went ahead to be ready to be tested on a CFA to confirm the measurement model and to be tested on a SEM to test hypothesized relationships. This was a multi step process which not only provided the necessary ethical protection but also applied technical rigor such that the data that were gathered were ethically acceptable and statistically valid to be used in the subsequent analysis.

RESULTS

The analysis was carried out in two steps of SEM which included measurement model and structural model. Initially, descriptive statistics was calculated to determine the baseline perceptions. The average scores indicated a positive perception with high strength, with PU (M = 3.794, SD = 0.779) and AIF (M = 3.770, SD = 0.799) being the most powerful ones.

Table 1: Descriptive Statistics for Variables

Item	Mean	SD
Attitude Toward Use (ATT)	3.709	0.787
Self-Efficacy (SE)	3.693	0.80
AI Familiarity (AIF)	3.770	0.799
Perceived Ease of Use (PEU)	3.674	0.732
Perceived Usefulness (PU)	3.794	0.779
Perceived Ethical Concerns (PEC)	3.694	0.808
Institutional Support (IS)	3.648	0.787
Perceived Personalization (PP)	3.624	0.80
Note: 1 = Strongly Disagree 5 = Strongly Agree		

To identify reliability and validity, CFA was used. Factor loadings were more than 0.77 and the alpha values of Cronbach were over 0.85, the CR values were over 0.88 and the AVE values were over 0.70 indicating convergent validity. The Fornell Larcker criterion was applied to test discriminant validity by indicating that the square root of AVE of each construct should surpass the inter-construct relationships. All constructs met this requirement and created a certain distinction between them.

Table 2: Results of CFA for TAM Measurement Model

Variable	Item	Internal Reliability Cronbach's Alpha	Convergent validity		
			Factor Loading	Composite Reliability	Average Variance Extracted (AVE)
AI Familiarity	AIF1	0.902	0.849	0.89	0.729

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	AIF3		0.872		
	AIF4		0.841		
Self-Efficacy	SE2	0.935	0.909	0.899	0.817
	SE4		0.898		
Institutional Support	IS1	0.945	0.899	0.945	0.812
	IS2		0.909		
	IS3		0.909		
	IS4		0.887		
Perceived Usefulness	PU1	0.959	0.921	0.959	0.854
	PU2		0.922		
	PU3		0.928		
	PU4		0.926		
Perceived Ease of Use	PEU1	0.891	0.905	0.929	0.812
	PEU2		0.896		
	PEU3		0.903		
Perceived Ethical Concerns	PEC1	0.946	0.855	0.946	0.815
	PEC2		0.916		
	PEC3		0.91		
	PEC4		0.927		
Attitude Toward Use	ATT2	0.778	0.913	0.881	0.787
	ATT3		0.86		
Perceived Personalization	PP1	0.919	0.823	0.922	0.748
	PP2		0.896		
	PP3		0.881		
	PP4		0.857		

Table 3: Discriminant Validity of Variables

Variables	1	2	3	4	5	6	7	8
AIF	0.854							
SE	0.808	0.904						
IS	0.794	0.871	0.901					
PU	0.786	0.827	0.819	0.924				
PEU	0.812	0.827	0.84	0.882	0.901			
PEC	0.631	0.684	0.687	0.697	0.648	0.903		
ATT	0.75	0.776	0.772	0.836	0.841	0.633	0.887	
PP	0.853	0.802	0.841	0.755	0.813	0.645	0.744	0.865
Mean (M)	3.77	3.693	3.648	3.794	3.674	3.694	3.709	3.624
Standard Deviation (SD)	0.799	0.800	0.787	0.779	0.732	0.808	0.787	0.800

The model fit was evaluated based on indices of chi-square/df, TLI, CFI and RMSEA. Acceptable thresholds were given in Eq.6,

$$\chi^2/df < 3 \quad TLI > 0.90 \quad CFI > 0.90 \quad RMSEA < 0.08 \qquad (5)$$

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The measurement model achieved excellent fit (χ^2/df = 1.892, TLI = 0.928, CFI = 0.940, RMSEA = 0.020), confirming its robustness.

Structural Model Estimation

The second stage involved testing the hypothesized relationships using SEM. The model was estimated through maximum likelihood estimation. The explanatory power of the structural model was assessed using the R^2 were given in Eq.7,

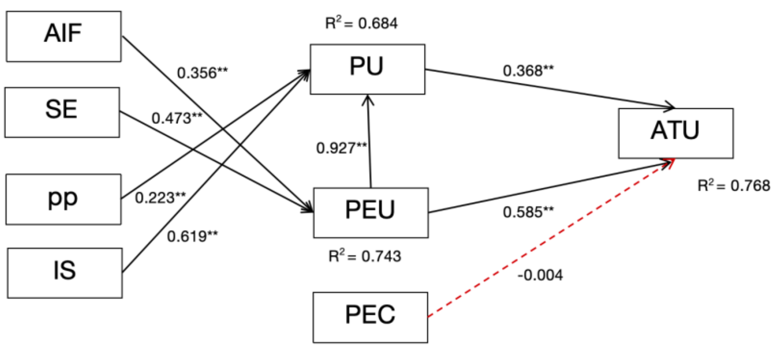
$$R^2 = 1 - \left(\Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2 \right) \quad (6)$$

Results showed strong explanatory power across constructs: PU (R^2 = 0.684), PEU (R^2 = 0.743), and ATT (R^2 = 0.768). These values demonstrated that the STAM model explained a substantial proportion of variance in students' attitudes and behavioural intentions toward AI adoption. Ethical concerns (PEC) were identified as a moderating variable, influencing the strength of some relationships without undermining overall model integrity.

Table 5: Fit indices and explanatory power of the structural model for STAM

Fit Index	STAM	Recommended criteria
TLI	0.928	>0.9
NNFI	0.928	>0.9
NFI	0.924	>0.9
CFI	0.940	>0.9
RMR	0.961	>0.9
RMSEA	0.020	<0.05
Explanatory power (R^2)		
PU	0.684	
PEU	0.743	
ATT	0.768	

Model fit indices for the structural model reinforced these findings: TLI = 0.928, CFI = 0.940, RMSEA = 0.020, all within recommended thresholds. Together, these results confirmed the validity of the extended TAM framework and highlighted the critical role of institutional and ethical factors in shaping student adoption of AI in education.



Note: Path coefficients are standardized. *** p < 0.001, ** p < 0.01. R^2 values indicate the variance explained in the dependent variables.

Figure 3- Structural Model with Path Coefficients and R² Values

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Based on the empirical results of the structural equation modeling analysis, the hypothesized relationships within the research model were largely supported. Of the eight hypotheses proposed in the research model, seven were empirically supported, while one was not supported by the data analysis.

As shown in the conceptual path model, six positive hypotheses (H1, H2, H3, H4,H5, H6, H7) were confirmed, indicating significant positive influences among the constructs. As illustrated in Figure 3, the path coefficients and their significance levels demonstrate strong support for the majority of the proposed hypotheses. The relationships between AI Familiarity (AIF) and Perceived Ease of Use (PEU), Self-Efficacy (SE) and PEU, Perceived Usefulness (PU) and Attitude toward Using (ATT), as well as the influence of PEU on PU, were all found to be statistically significant and positive, as indicated by the robust path coefficients (ranging from 0.356** to 0.927**) and high explanatory power ($R^2 = 0.684$ for PU and $R^2 = 0.768$ for ATT). These results confirm the critical role of both external variables (AIF and SE) and core TAM constructs (PEU and PU) in shaping users' behavioral intentions toward AI technology reuse.

However, the analysis revealed one notable exception: Hypothesis 8 (H8), which proposed a negative influence of Perceived Ethical Concerns (PEC) on Attitude toward Using (ATT), was not supported by the data ($\beta = 0.004$, $p > 0.05$). In conclusion, the overall model demonstrates strong predictive validity, with the majority of hypotheses receiving empirical support.

Significant Contribution to the Body of Knowledge

This study contributes to the growing body of knowledge on AI adoption in higher education by extending the traditional Technology Acceptance Model (TAM) with five context-relevant constructs: AI Familiarity, Self-Efficacy, Perceived Personalization, Institutional Support, and Perceived Ethical Concerns. By empirically validating this extended model using a large sample of digitally active Chinese university students, the research provides one of the first evidence-based assessments of how institutional and ethical factors integrate with classical TAM determinants to shape attitudes toward AI-based learning tools. The Structural Equation Modeling results offer new theoretical insights on the predictive power of personalization and institutional support while demonstrating that ethical concerns, although widely discussed in existing literature, do not significantly deter student attitudes in practice. These contributions deepen theoretical understanding and support the design of sustainable and responsible AI integration strategies in education.

DISCUSSION

The implications of the research offer important insights into how Chinese higher education students accept and use AI-based learning aids,, from the perspective of the extended TAM. The demographic profile shows that most of the respondents were young undergrads from computer science and information technology disciplines with a high level of previous exposure to AI aids. This demographic composition not only verifies the fact that the sample represents digitally literate students but also highlights the growing significance of AI to students with future careers in AI-based fields. Interestingly, although almost 89% indicated they used AI, only 45.67% felt highly knowledgeable about it, while 41.23% said they had limited knowledge. This disparity mirrors the general difficulty of AI adoption among students: they might easily embrace AI tools for practical tasks but lack deeper conceptual insight into how such technologies work, mirroring previous studies that indicated superficial adoption behaviours among students (Bozkurt et al., 2021; Chiu et al., 2023).

Descriptive statistics also shed light on student attitudes. Perceived usefulness (PU) was the most salient construct ($M = 3.794$), followed by AI familiarity ($M = 3.770$), indicating that the students highly regarded the instrumental value AI brings to learning. This is consistent with Haleem et al. (2022) and Rahman and Watanobe (2023), who posit that students overwhelmingly situate AI adoption in terms of its potential to improve efficiency, productivity, and information accessibility. Yet, perceived personalization ($M = 3.624$) was the lowest, noting that although AI tools are viewed as being helpful, they are not yet regarded as responsive to personal needs of learning. This is in agreement with Zhu et al. (2023), who noted that the personalization abilities of existing AI models are still underdeveloped, often delivering generic outputs in place of personalized feedback.

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CFA confirmed the stability of the measurement model, with high factor loadings (>0.77), Cronbach's alpha coefficients (>0.82), and composite reliabilities (>0.88), ascertaining internal consistency between constructs. The high average variance extracted (AVE > 0.70) illustrates convergent validity, with discriminant validity met for all constructs, suggesting conceptual distinctness. These results support the theoretical foundations of TAM in reflecting complex dimensions of student acceptance and affirm the applicability of TAM within tertiary education settings. The good model fit statistics (TLI = 0.928, CFI = 0.940, RMSEA = 0.020) further validate that the assumed associations were empirically supported.

The structural model findings offer greater insights into student attitude determinants. Perceived usefulness (R^2 = 0.684) and perceived ease of use (R^2 = 0.743) were both strongly explanatory, suggesting that students' positive attitude towards AI was strongly influenced by their perception of its usability and ease of use. This corroborates the original TAM model (Davis, 1989) and broadens its applicability to modern-day AI usage. Interestingly, ATT had the strongest explanatory power (R^2 = 0.768), indicating that the TAM model taps into psychological and behavioural factors driving student preparedness for AI uptake. The results are in tandem with Rodway and Schepman (2023), who established that AI learning technologies significantly predict student satisfaction and subsequent learning engagement.

Interestingly, one finding of the study was the influence of PEC. Although PEC did not severely compromise the model's explanatory power, it served as a moderating variable that affected the intensity of some relationships. Students were concerned about plagiarism, misuse, and equity when applying AI, similar to the concerns raised by Huallpa (2023) and Kooli (2023), who emphasized the need to integrate ethical controls into AI integration plans. This means that institutions must face ethical issues if they try to promote responsible and sustainable AI adoption. Also supporting this, is the fact that institutional support (IS) is identified as the most significant predictor. This relates to the finding that students' confidence levels for using AI in education increase when they are given guidance and clear policies (Holmes et al., 2021) and this is consistent with UNESCO's global policy guidelines for AI.

A second important finding was the relatively lower score for perceived personalization. While students recognized the general value of AI, they were wary of its ability to deliver personalized paths to learning. This is consistent with Williamson and Eynon (2020) who made the argument that current AI systems threaten to reinforce standardized models of learning rather than supercharge differentiated pedagogies. A closed loop will be achieved by future generations of AI tools that incorporate adaptive courseware that can react to individual student needs.

Taken together, the findings indicate that students' attitudes to the adoption of AI are generally positive, but are qualified by knowledge gaps, ethical concerns and a lack of personalization. The extended TAM framework provides a robust framework to describe these dynamics, confirming both that utility and ease of use are important drivers, but that ethical and institutional factors affect contextual readiness. Significantly, the research highlights a dual challenge facing policymakers and teachers: that while AI clearly has great potential to transform education, it must be implemented through mechanisms that simultaneously enable innovation, equity, and ethics. Placing these findings into the broader discussion, this research both empirically informs and theoretically advances the discussion to emphasize the importance of preparing higher education for an AI-driven future.

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