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MANAGING THE DIGITAL TRANSFORMATION OF HIGHER EDUCATION: THE IMPACT OF AI LITERACY AND COGNITION ON THE ADOPTION OF INTELLIGENT TEACHING SYSTEMS

GERENCIANDO A TRANSFORMAÇÃO DIGITAL DO ENSINO SUPERIOR: O IMPACTO DA ALFABETIZAÇÃO EM IA E DA COGNIÇÃO NA ADOÇÃO DE SISTEMAS DE ENSINO INTELIGENTES

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Abstract
In the digital transformation of higher education, AI technology is seen as an effective way to address the imbalances in resource inequality, lagging teaching evaluation, and insufficient student-teacher interaction in multimedia classrooms. This study explores students' willingness and actual behavior to adopt AI, particularly in multimedia classrooms. Focusing on influencing factors such as AI literacy, perceived usefulness/ease of use, and perceived risk, the study analyzes how these factors collectively shape students' AI use behaviors. Empirical evidence shows a significant positive correlation between AI application and improved student academic performance and teaching effectiveness. Based on these variables, the study explores the factors influencing AI adoption among college students and constructs and validates a hypothetical model, providing theoretical support and practical guidance for universities to promote the deep integration of AI into education and teaching.
Keywords: Artificial Intelligence Literacy. Perception. Multimedia Classroom.

Resumo
Na transformação digital do ensino superior, a tecnologia de IA é vista como uma forma eficaz de lidar com os desequilíbrios na desigualdade de recursos, a avaliação de ensino defasada e a interação insuficiente entre alunos e professores em salas de aula multimídia. Este estudo explora a disposição e o comportamento real dos alunos em adotar a IA, particularmente em salas de aula multimídia. Com foco em fatores influentes, como alfabetização em IA, utilidade/facilidade de uso percebidas e risco percebido, o estudo analisa como esses fatores, coletivamente, moldam os comportamentos de uso da IA pelos alunos. Evidências empíricas mostram uma correlação positiva significativa entre a aplicação da IA e a melhoria do desempenho acadêmico dos alunos e da eficácia do ensino. Com base nessas variáveis, o estudo explora os fatores que influenciam a adoção da IA entre estudantes universitários e constrói e valida um modelo hipotético, fornecendo suporte teórico e orientação prática para que as universidades promovam a integração profunda da IA na educação e no ensino.

Palavras-chave: *Alfabetização em Inteligência Artificial. Percepção. Sala de Aula Multimídia.*

1 INTRODUCTION

In recent years, artificial intelligence (AI) technology has developed rapidly, achieving significant results in many key areas. Despite facing challenges such as privacy and ethical considerations, it has been deeply integrated into multiple industries and can now provide personalized guidance in education and training. At the same time, higher education is undergoing a digital transformation encompassing teaching, management, and research. Multimedia classrooms, as part of this transformation, while enriching the presentation of teaching content, face challenges such as poor interactive learning. Furthermore, their application is plagued by issues such as uneven resource allocation and outdated content, limiting their contribution to higher education's digital transformation.

Currently, there is a significant gap between the transformative potential of AI-powered multimedia classrooms and their actual teaching effectiveness, and existing research lacks relevant empirical interdisciplinary studies. Based on this, this study focuses on the application of AI technology in multimedia classrooms. By exploring the impact of factors such as AI literacy and perceived usefulness on students' willingness to adopt AI and their actual use behaviors, this study proposes relevant models and frameworks, providing empirical evidence and policy recommendations for the development of higher education. This research is of great theoretical and practical significance and is expected to make multifaceted contributions to educational development.

2 LITERATURE REVIEW AND PROBLEM HYPOTHESIS

2.1 The concept and application of artificial intelligence technology

Artificial intelligence (AI) is the science of researching and developing methods to simulate and expand human intelligence. Its core objective is to empower computers with learning and reasoning capabilities through machine learning algorithms. The "Turing Test" laid the philosophical foundation for this field in 1950, and the term "artificial intelligence" was coined in 1956, marking the birth of the discipline. Today, AI is widely used in various fields.

According to its capabilities and versatility, AI is divided into three categories: weak artificial intelligence (ANI, a single field, such as AlphaGo, voice and image recognition, with wide but limited applications in education), strong artificial intelligence (AGI, close to human level, with great educational potential but no practical application), and super artificial intelligence (ASI, far exceeding human intelligence, with forward-looking educational applications but raising concerns about dominance).

The application of AI in education is positive: the market is expanding and growing at a high rate; in terms of personalized learning, it accurately analyzes learning situations, customizes learning paths, and adjusts teaching in real time (scholarly research confirms its positive effects); classroom applications include adaptive learning systems (such as Knewton's recommendation of adaptive materials), intelligent tutoring systems (real-time support), and intelligent teaching assistants (assisting teaching management, with proven multi-disciplinary applications).

Professor Meyer's multimedia learning theory provides a perspective for the integration of AI and multimedia. In summary, existing literature demonstrates how AI can transform traditional teaching, laying the foundation for the integration of AI and multimedia classrooms and highlighting the need for research on optimizing applications in higher education. Currently, AI applications in education are growing and diverse, facilitating the transformation of teaching towards personalized, efficient, and data-driven learning, laying the foundation for intelligent education models.

2.2 Characteristics and current status of multimedia classrooms supported by artificial intelligence technology

In the field of education, AI and multimedia are integrated into AI-supported multimedia classrooms: in terms of technical integration, it optimizes teaching presentation, improves teacher skill requirements, and realizes intelligent assessment; the interaction includes three dimensions: teacher-student (AI helps to understand learning situation), student-student (AI assists in grouping), and human-computer (teaching assistants answer questions and recommend resources). It is highly adaptable, intelligent and interactive, laying the foundation for innovation in higher education.

In university settings, there is a significant contrast between traditional teaching (teacher-centered, with weak interaction, lack of personalization, and single resources, Zhang Zhen et al., 2002-2013) and multimedia classrooms (integrating multiple forms of information, reducing the difficulty of understanding, increasing participation, and having good interdisciplinary effects, Xu Aiping et al., 2001-2024). However, multimedia classrooms have problems with resources and teachers' acceptance of AI (influenced by the TAM model, Davis, 1989).

In summary, traditional classrooms face challenges, and multimedia integration provides solutions; AI multimedia classrooms have good prospects but are constrained by resources, facilities, and teacher level. Solving these problems is crucial to digital innovation in higher education.

2.3 Literature review on artificial intelligence technology in higher education

The application of AI in higher education is a key topic in educational technology. Existing research on AI literacy, perceived usefulness/usability, perceived risk, intention to use, and actual use aligns with the variables in this study's conceptual framework. The following section examines the research from each variable dimension and analyzes the internal connections using the TAM, TPB, and TRA models.

AI literacy: Students' foundational abilities to embrace intelligent technology (including technical knowledge, operational skills, and risk awareness). Li Honggang (2023) noted that understanding AI concepts influences judgments about the value of technology; Zuo Yi (2024) found that students who can use intelligent translation tools have higher classroom engagement (aligning with TAM); and Chen Fang (2019) proposed that awareness of AI privacy risks reduces willingness to use (aligning with TPB).

Perceived usefulness: Students' subjective judgment of AI's value drives usage intention. Studies by Na Weicong et al. (2024), Anwei (2024), and Lin Mengyao et al. (2021) validated its positive impact (aligned with TAM and TRA) through virtual simulation, incorrect question recommendation, and real-time question answering.

Perceived ease of use: Focus on operational convenience and lower the barrier to entry. Hao Wenting (2015) found that complex operations lead to resistance, while one-click tools have a high usage rate (aligning with TAM). Yang Lin et al. (2021) proposed that AI training can improve operational proficiency (aligning with TPB).

Perceived Risk: Students' concerns about the negative impacts of AI inhibit their intention to use it. Studies by Ying Guoliang et al. (1999) and Zhao Xiaoqing (2009) verified its negative impact from the perspectives of privacy risks and doubts about content accuracy, respectively (consistent with the TPB).

Intention to use: An important antecedent of actual use. Zhang Zhen (2002) verified that it directly leads to behavior (consistent with TRA); Zhu Yinghui (2016) found that science and engineering students had a higher rate of intention-to-behavior conversion.

In summary, AI literacy and perception variables significantly influence usage intention and actual use, consistent with relevant theories. However, existing research has tended to focus on single variables and has not examined their interactions. This study will address this gap by using empirical data to examine the interplay of these variables.

2.4 Theoretical basis

Existing literature demonstrates that AI literacy and perceived variables (usefulness, ease of use, and risk) significantly influence both intention and actual use, highly consistent with theories such as TAM, TPB, and TRA. However, existing research has largely focused on single variables, lacking the ability to examine interactions between them. This study, building on existing research, will investigate the interplay of these variables through empirical data, addressing this research gap. This study is based on the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Theory of Reasoned Action (TRA). These three frameworks provide robust support for analyzing university students' acceptance and use of AI technology in multimedia classrooms and are key to the conceptual framework.

TAM (Davis, 1989): The core is perceived usefulness (users' perception of the benefits of technology, such as AI tools improving learning efficiency) and perceived ease of use (the perception of the difficulty of using technology, such as the simplicity of the interface). Both influence user attitudes and behavioral intentions, which in turn influence actual usage through intentions. External variables can regulate these two perceptual variables, and their effectiveness has been verified in studies such as online learning platforms.

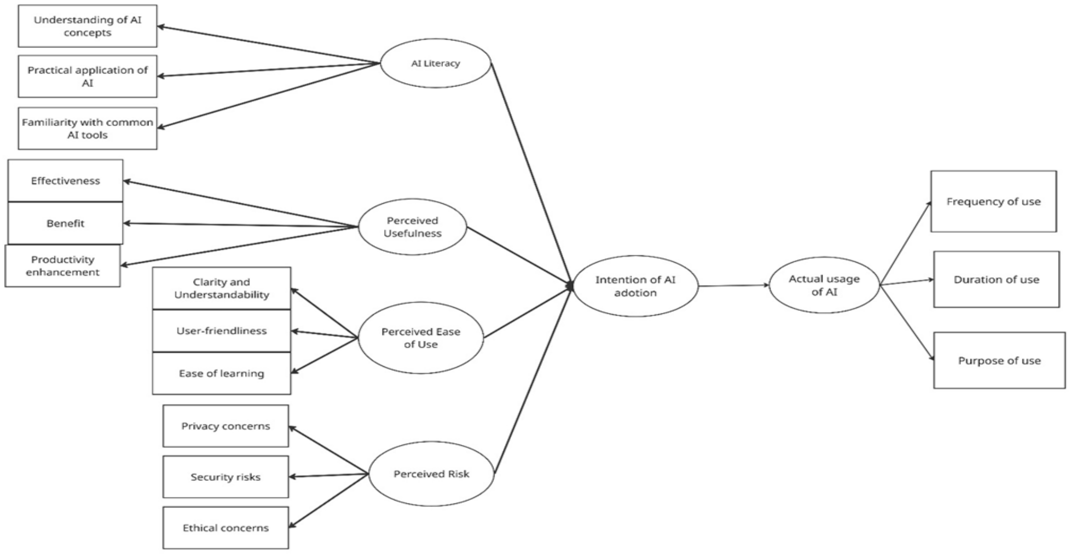
TPB (Ajzen, 1988, 1991): Originated from TRA, it believes that behavior is the result of careful consideration. Behavioral intention is influenced by behavioral attitude (positive and negative feelings about the behavior), subjective norms (perceived pressure to behave), and perceived behavioral control (experience and potential obstacles). The more positive or stronger these three are, the higher the intention (for example, students have a positive attitude towards AI, have support from others, and are able to use it, which leads to higher intention).

TRA (Fishbein and Ajzen, 1975): focuses on the conscious influence of attitudes on behavior. It assumes that people are rational and that behavioral intentions depend on behavioral attitudes (positive and negative emotions toward the behavior) and subjective norms (expectations of important others), which in turn affect actual behavior. However, it implies the premise that "people can fully control their behavior." Later, Ajzen added perceived behavioral control to develop it into TPB.

In this research context, each of the three approaches has its own focus: TAM focuses on the perception of technological features, TPB examines influencing factors from multiple dimensions, and TRA explains the logic of intention formation. Combining these three approaches creates a comprehensive theoretical framework for exploring university students' acceptance and application of AI technology in multimedia classrooms, identifying key influencing factors and providing a solid foundation for research hypotheses and empirical research.

2.5 Conceptual framework model

Figure 1



3 RESEARCH METHODS

3.1 Research methods

This study employed a mixed methods approach and a sequential explanatory design, combining quantitative and qualitative approaches to explore the factors influencing student adoption of AI technology in multimedia-rich university classrooms. In the first phase, a quantitative survey of students at a public university in Kunming was conducted using a stratified random sampling approach. Data were collected using a validated structured questionnaire (including a Likert scale). Structural equation modeling (SEM) was used to test hypothesized relationships between variables such as AI literacy and perceived usefulness. In the second phase, semi-structured interviews were conducted with experts, faculty, and students. The quantitative results were interpreted through thematic analysis, focusing on contextual factors. Finally, the data were integrated to deepen our understanding of AI applications in higher education.

3.1.1 Quantitative research methods

Data was collected through questionnaires and test score analysis: the questionnaire was based on the method of Cai Shaolin et al. (2024), and a multidimensional scale (including a Likert scale) was designed to quantify subjective feelings and collect feedback on a large scale; the score analysis referred to the method of Mo Hongwei et al. (2013), comparing the scores of the experimental group and the control group, and using statistical methods such as the Z test to evaluate the impact of AI technology on learning outcomes and enhance the objectivity of the conclusions.

3.1.2 Qualitative Research Methods

Use interviews and classroom observations to understand the actual situation: Interviews draw on the methods of Liu Haibo and Shen Jing (2008), using face-to-face open-ended questions and follow-up to gain real experience for optimized application; classroom observations refer to the practices of Kang Meijuan (2008), developing detailed scales to record teaching behaviors, learning performance and interactions, obtaining first-hand information to reveal potential problems.

3.1.3 Mixed research methods

Drawing on the methods of Chen Miko and Gu Xiaodong (2021), this paper combines quantitative and qualitative research: quantitative research verifies hypotheses at the macro level (such as the impact of AI on academic performance), and qualitative research explores causes at the micro level (such as users' subjective experience). The two complement each other, improve the comprehensiveness and reliability of the results, and provide a powerful tool for the implementation and exploration of AI technology in university multimedia classrooms.

3.2 Sampling method

3.2.1 Qualitative stage

The project uses semi-structured interviews and plans to select 12-15 key respondents through purposive sampling, including subject experts, university teachers and students in AI-supported educational environments. The selection criteria are the respondents' experience and involvement with AI technology in the field of higher education.

3.2.2 Quantitative stage

The population of this quantitative stage is all students who take multimedia courses. The sample size is calculated using the Cochran formula, which is as follows:

$$n_0 = \frac{Z^2 \cdot p \cdot (1-p)}{e^2} \tag{1}$$

In the formula, n0 is the initial sample size for an infinite population; z is the z-score corresponding to the confidence level (1.96 at a 95% confidence level); p is the estimated proportion of the target attribute in the population (set to 0.5 when unknown to ensure maximum variability); and e is the margin of error (set to 0.05 in this example). Substituting these into the calculation yields 385.

Given that the total population (N) is 1,200 students, the final sample size will be adjusted using a finite population correction:

$$n = \frac{n_0}{1 + \frac{n_0 - 1}{N}} \tag{2}$$

The sample size for this study was approximately 292 students. The selection process involved two steps: first, stratification by major, encompassing a wide range of disciplines, including science, engineering, humanities, and business: For science and engineering, students selected Computer Science and Technology (42) and Electronic Information Engineering (55); for humanities, students selected Chinese Language and Literature (45) and English (55); and for business, students selected Business Administration (50) and Accounting (45), ensuring a diverse range of students. Second, stratification by grade level was performed, with students randomly selected from freshman to senior year within each major to reflect the learning profiles and AI acceptance of different grades.

This study used multi-dimensional random sampling to ensure sample diversity and representativeness, selecting students from a variety of disciplines and grades. The final sample included 292 students from six majors, evenly distributed from freshman to senior year. The sample size by major and academic year is as follows:

Table 1

Major	First Year	Second Year	Third Year	Fourth Year	Total
Computer Science and Technology	10	11	10	11	42
Electronic Information Engineering	15	15	15	10	55
Chinese Language and Literature	11	12	11	11	45
English	14	14	13	14	55
Business Administration	12	13	12	13	50
Accounting	10	10	10	15	45
Total	72	75	71	74	292

Through this structured sampling method, an evenly distributed and balanced research sample was obtained, ensuring that the research results reflected students from different disciplines and grades.

3.3 Data collection methods and process

3.3.1 Questionnaire design

The questionnaire underwent multiple rounds of optimization (refer to Cai Shaolin et al., 2024; combined with the literature), and its dimensions included students' attitudes towards AI multimedia teaching, learning experience, and application evaluation. A Likert scale was used to measure attitudes, experience, and satisfaction with intelligent functions, and open-ended questions were included to solicit suggestions. Before formal distribution, 50 similar students were selected for a preliminary survey, and the wording and options were optimized to ensure quality.

3.3.2 Interview design

A semi-structured methodology (see Liu Haibo and Shen Jing, 2008) was used to interview teachers and students about their experiences, feelings, and suggestions for AI multimedia teaching. Teacher interviews focused on teaching adjustments, application difficulties, and AI resource integration. Student interviews focused on learning experiences, impact on interest, and the impact of AI on independent and collaborative learning. Interviews lasted 30-60 minutes, and were recorded and analyzed promptly to obtain qualitative data.

3.4 Data Collection analysis methods

3.4.1 Quantitative data analysis

Use SPSS for descriptive statistics (calculating means and standard deviations); use software such as AMOS/SmartPLS to analyze variable relationships using SEM: first evaluate the reliability and validity of the measurement model through CFA, and then analyze the structural model (focusing on path coefficients and testing hypotheses).

3.4.2 Qualitative data analysis

Thematic analysis was conducted using NVivo: the text was transcribed and initially coded, the themes and sub-themes were summarized, the themes were interpreted and analyzed in combination with the data to provide qualitative support for the conclusions.

3.4.3 Insights from mixed methods.

A sequential explanatory mixed methods approach was employed: quantitative analysis using SEM (to lay the foundation for qualitative analysis) followed by thematic analysis using NVivo (to integrate insights and develop recommendations) to achieve a comprehensive understanding of the research questions.

3.5 Ethical considerations

Strict ethical guidelines were followed: participants were required to provide informed consent (voluntary participation, with the option to withdraw at any time without negative consequences); data were stored in encrypted form (accessible only to the research team); questionnaires and interviews avoided sensitive questions, encouraged truthful expression, and respected personal opinions.

4 DATA ANALYSIS

4.1 Quantitative results and discussion

Table 2

	variable	serial number
independent variable	Artificial Intelligence Literacy	AIL
	Perceived Usefulness	PU
	Perceived Ease of Use	PEU

	Perceived Risk	PR
mediating variable	Usage Intention	AIIA
dependent variable	Actual Usage	AU

4.1.1 Descriptive statistics

To fully understand the basic characteristics of the survey sample, this study conducted descriptive statistical analysis of respondents' gender, grade, major, and whether they had used artificial intelligence (AI) technology in class. By compiling and analyzing the data from 292 valid questionnaires, we can gain a preliminary understanding of the overall composition of the sample, providing a foundation for further exploration of the relationships between variables. Table 1 shows the frequency and percentage of each variable, and a detailed analysis is provided below:

Table 3

Descriptive statistics results

Demographic		frequency	percentage
Gender	Male	137	46.9
	Female	132	45.2
	Other	23	7.9
	total	292	100.0
Grade	Freshman	72	24.7
	Sophomore	75	25.7
	Junior	71	24.3
	Senior	74	25.3
	total	292	100.0
Field of Study	Science and Engineering	97	33.2
	Liberal Arts	100	67.5
	Business	95	100.0
	total	292	
	Yes	243	83.2
	No	49	16.8

Have you used AI technology (such as intelligent teaching platforms, personalized learning systems, etc.) in class?	total	292	100

1) Gender distribution analysis

This study collected 292 valid questionnaires, with the gender distribution being: 137 males (46.9%), 132 females (45.2%), and 23 “other” genders (7.9%). The gender ratio is balanced, which is basically consistent with the gender composition of college students. The “other” gender ratio reflects the inclusive and personalized trend of college students’ gender identity.

This distribution provides a grouping basis for analyzing gender differences in AI technology use. Previous research has shown that different genders exhibit distinct technology adoption characteristics (e.g., men tend to be more proactive in exploration, while women prioritize ease of use and assistance). Observing these differences is crucial for accurately matching teaching resources and optimizing AI promotion strategies. While the "Other" gender group represents a small but significant proportion, their AI usage preferences and barriers warrant further exploration, enriching gender research and promoting the equitable and inclusive development of AI in education.

In summary, the gender variable has structural balance and research value. Further comparison of the frequency, type, and satisfaction of AI use among different gender groups can deepen our understanding of the mechanism of action of AI education and provide empirical evidence for personalized teaching and technological intervention.

2) Grade distribution analysis

This survey covered university students from four grades, with a sample distribution of 72 freshmen (24.7%), 75 sophomores (25.7%), 71 juniors (24.3%), and 74 seniors (25.3%). Each grade level represented approximately 25%, creating a balanced structure and laying the foundation for analyzing differences in AI acceptance and usage among students at different stages of study. Grade level influences students' learning tasks and planning, leading to varying purposes, reliance, and ethical awareness of AI use. Freshmen tend to use AI as a learning aid (e.g., summarizing courseware and researching resources); juniors and seniors tend to use AI for more advanced tasks (e.g., drafting papers and processing data). Senior students also have a stronger awareness of the norms and ethics of AI use, while younger students prioritize the tool's convenience.

Subsequently, variance analysis (ANOVA) or interaction analysis can be conducted by grouping by grade to explore the relationship between the degree of AI usage, dependence and grade, and provide a theoretical basis for the phased implementation of AI technology education in colleges and universities.

3) Professional distribution analysis

The survey respondents were divided into three major categories: 97 (33.2%) in science and engineering, 100 (34.2%) in liberal arts, and 95 (32.5%) in business. Although some percentages contain statistical logic errors, the distribution of the number of people is balanced, providing the possibility to analyze the differences in AI usage among students of different majors.

Professional background influences the path and frequency of AI use: Science and engineering students, whose courses involve programming and modeling, are more likely to use AI language models and code assistance tools, and can evaluate the quality of AI output; liberal arts and business students tend to prefer non-technical functions such as writing assistance, translation, and data integration.

Teachers in different majors integrate AI differently in their teaching: business teachers are encouraged to use AI to simulate market analysis and financial modeling, while liberal arts teachers often use AI for paper draft generation and semantic analysis. The professional and technical cultural atmosphere and tool availability also affect students' AI usage habits.

Major classification is both a fundamental descriptive variable and an important variable in explaining differences in AI usage behavior. Subsequent research will explore significant differences in AI usage frequency, functional types, and effectiveness across different majors, as well as underlying factors such as educational resource allocation, curriculum structure, and disciplinary characteristics.

4) **Have you used AI technical analysis?**

In this survey, 243 students (83.2%) answered that they had used AI technology in class, and 49 students (16.8%) answered that they had not used it. This shows that AI classroom applications have become popular among the surveyed college students, and most students have used tools such as ChatGPT and AI translation.

This result has practical implications: First, from a student perspective, it demonstrates the rapid penetration of AI into university teaching. Especially with the widespread adoption of generative AI in 2022, AI-assisted learning has become a requirement for some courses, no longer exclusive to a select few. Second, the high percentage reflects students' high acceptance of AI and suggests that educators have integrated AI into the classroom to a certain extent. However, further research is needed to explore whether this high frequency of use leads to dependency and truly improves learning quality. The 16.8% of "non-users" may be due to technical barriers, ethical concerns, and other factors; the gap between their attitudes and their technology warrants further study.

In summary, this variable not only reflects the current status of AI usage, but also provides a key basis for subsequently building user portraits and analyzing differences in learning effects.

Table 4

Descriptive statistical results

	average value	standard deviation	Skewness		kurtosis	
	statistics	statistics	statistics	standard error	tatistics	standard error
AIL1	3.288	1.316	-.325	.143	-1.016	.284
AIL2	3.312	1.236	-.292	.143	-.919	.284
AIL3	3.315	1.278	-.309	.143	-.982	.284
AIL4	3.267	1.286	-.324	.143	-.948	.284
AIL	3.295	1.198	-.220	.143	-1.144	.284
PU1	2.801	1.122	.251	.143	-.668	.284
PU2	2.801	1.043	.186	.143	-.715	.284
PU3	2.842	1.076	.251	.143	-.667	.284
PU4	2.846	1.140	.404	.143	-.700	.284
PU	2.823	1.023	.284	.143	-1.040	.284
PEU1	3.240	1.095	-.345	.143	-.404	.284
PEU2	3.216	1.057	-.405	.143	-.318	.284
PEU3	3.233	1.055	-.195	.143	-.432	.284
PEU4	3.236	1.095	-.417	.143	-.362	.284
PEU	3.231	.988	-.256	.143	-.741	.284

PR1	2.973	1.139	-.227	.143	-.671	.284
PR2	2.983	1.063	-.190	.143	-.527	.284
PR3	2.959	1.108	-.178	.143	-.589	.284
PR4	3.031	1.079	-.227	.143	-.517	.284
PR	2.986	1.011	-.146	.143	-.992	.284
AIIA1	3.113	1.083	-.276	.143	-.663	.284
AIIA2	3.168	1.060	-.322	.143	-.477	.284
AIIA3	3.123	1.015	-.369	.143	-.424	.284
AIIA	3.135	.961	-.187	.143	-.983	.284
AU1	3.147	1.147	-.360	.143	-.427	.284
AU2	3.099	1.094	-.420	.143	-.419	.284
AU3	3.127	1.158	-.396	.143	-.544	.284
AU	3.124	1.054	-.320	.143	-.663	.284

According to the descriptive statistics in Table 4, the sample distribution of each measured variable is normal and the discrimination is good. In terms of average values: Artificial Intelligence Literacy (AIL) is 3.295 (above average), Perceived Usefulness (PU) is 2.823 (below average, indicating reservations about the educational value of AI tools), Perceived Ease of Use (PEU) is 3.231 (slightly above PU, indicating that AI tools are easy to use), Perceived Risk (PR) is 2.986 (close to the average, indicating concerns about use), Artificial Intelligence Adoption Intention (AIIA) is 3.135 (positive attitude towards future use), and Actual Application of AI (AU) is 3.124 (some actual use has already occurred).

The standard deviations are all approximately 1, reflecting inter-individual variability. The skewness of most variables is small in absolute value, indicating generally symmetrical data. The kurtosis is mostly negative, indicating a flat distribution with no extreme concentration. In summary, the statistical characteristics of each variable provide a foundation for subsequent analysis and also demonstrate a gap between perceived value and usage behavior. Future efforts will require improvements in system functionality and risk management to enhance the acceptance and willingness to use AI teaching tools.

4.1.2 Reliability and validity analysis

Table 5

Reliability analysis results

variable	Cronbach Alpha	Cronbach's Alpha	Number of items
AIL	.953	.953	4
PU	.830	.838	4
PEU	.807	.808	4
PR	.852	.848	4
AIIA	.921	.946	3
AU	.922	.922	3

According to the reliability analysis in Table 3, the Cronbach's Alpha coefficients of all major variables exceeded 0.80, and the internal consistency and scale reliability were good: Artificial Intelligence Literacy (AIL) α = .953 (extremely high consistency), perceived usefulness (PU, α = .830), perceived ease of use (PEU, α = .807), and perceived risk (PR, α = .852) achieved good reliability (the reliability of the items in measuring constructs was high), and the reliability of Artificial Intelligence Adoption Intention (AIIA, α = .921) and Actual Application (AU, α = .922) was excellent (supporting the measurement validity of the mediating variables and dependent variables in subsequent structural modeling).

In summary, all variables have passed the reliability test, ensuring the stability and scientific nature of subsequent analysis results.

Table 6

Validity analysis results

variable	Items	load	KMO
AIL	AIL1	.965	.861
	AIL2	.925	
	AIL3	.929	
	AIL4	.928	
PU	PU1	.957	.866

	PU2	.930	
	PU3	.917	
	PU4	.932	
PEU	PEU1	.952	.849
	PEU2	.909	
	PEU3	.896	
	PEU4	.914	
PR	PR1	.953	.854
	PR2	.916	
	PR3	.909	
	PR4	.905	
AIIA	AIIA1	.915	.749
	AIIA2	.900	
	AIIA3	.925	
AU	AU1	.948	.748
	AU2	.924	
	AU3	.920	

According to the above table, all variable measurement items have passed the factor loading and KMO test, verifying the structural validity of the scale: the factor loadings of the artificial intelligence literacy (AIL) items are all over 0.92, KMO=0.861 (high convergent validity, suitable for factor analysis); the loadings of the perceived usefulness (PU) items are all over 0.91, KMO=0.866 (clear construct dimensions and strong indicator consistency); the loadings of the perceived ease of use (PEU) items are 0.896-0.952, KMO=0.849 (good convergent validity).

The item loadings of perceived risk (PR) exceeded 0.90, with a KMO of 0.854 (good factor extraction and structural adaptability). The item loadings of artificial intelligence adoption intention (AIIA, 3 items) exceeded 0.90, with a KMO of 0.749 (meeting the requirements of factor analysis). The item loadings of artificial intelligence practical application (AU) exceeded 0.92, with a KMO of 0.748 (valid scale structure).

In summary, the factor loadings of all variable measurement items are far higher than the 0.7 standard, and the KMO values are all over 0.7. The scale has good convergent validity and structural rationality, laying a solid measurement foundation for subsequent structural equation modeling analysis.

4.1.3 Correlation analysis

This study used the Pearson Correlation Coefficient to test the correlation between the main variables. The results are shown in the following table:

Table 7

Correlation analysis results

	AIL	PU	PEU	PR	AIIA	AU
AIL	1					
PU	.629**	1				
PEU	.494**	.542**	1			
PR	.431**	.623**	.813**	1		
AIIA	.399**	.436**	.665**	.422**	1	
AU	.421**	.494**	.455**	.484**	.336**	1

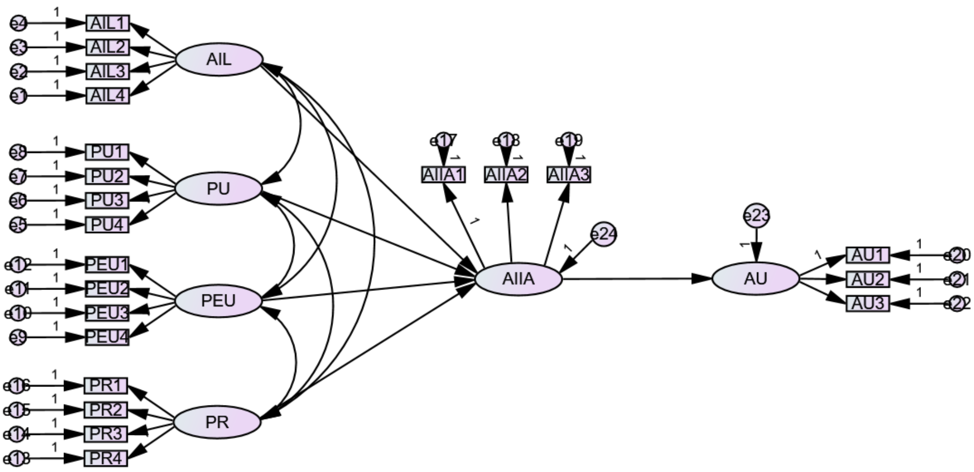
According to the correlation analysis in Table 3 (**p < 0.01), the six core variables of this study were all significantly positively correlated: the measurement items of each variable passed the factor loading and KMO test, and the structural validity met the standards: AIL (loading > 0.92, KMO=0.861), PU (loading > 0.91, KMO=0.866), PEU (loading 0.896-0.952, KMO=0.849), PR (loading > 0.90, KMO=0.854), AIIA (3 items, loading > 0.90, KMO=0.749), AU (loading > 0.92, KMO=0.748), all meeting the requirements of factor analysis.

In summary, all variable loadings were much higher than 0.7, KMO>0.7, and the scale had good convergent validity and structural rationality, laying the foundation for subsequent SEM analysis.

4.1.4 Evaluation of the structural model

To verify the rationality and fit of the constructed structural equation model, this paper uses AMOS software to estimate the model and evaluate the goodness of fit of the model from multiple dimensions, including chi-square statistics, relative fit index, residual analysis, information criterion, and approximate error index. The results are shown in the following table:

Figure 2



To verify the goodness of fit of the structural equation model constructed in this study, this paper used a variety of fit indices to evaluate the model, including chi-square test, residual and absolute fit index, comparative fit index, parsimony index, error approximation analysis, and information criterion index. The specific analysis is as follows:

Table 8

Model fit index results

Fit index classification	Indicator name	Value (this model)	Recommended standards	Fit evaluation
Chi-square test	CMIN	368.678	The smaller the better	acceptable
	DF	192	-	-

	CMIN/DF	1.920	< 3	good
	P value	0.000	> 0.05	acceptable
Residuals and Absolute Fit	RMR	0.262	< 0.08	generally
	GFI	0.899	≥ 0.90	better
	AGFI	0.867	≥ 0.90	better
	PGFI	0.682	≥ 0.50	good
comparative fit index	NFI	0.944	≥ 0.90	excellent
	RFI	0.933	≥ 0.90	excellent
	IFI	0.973	≥ 0.90	excellent
	TLI	0.967	≥ 0.90	excellent
	CFI	0.972	≥ 0.90	excellent
parsimony index	PRATIO	0.831	> 0.50	good
	PNFI	0.785	> 0.50	good
	PCFI	0.808	> 0.50	good
Error approximation analysis	RMSEA	0.056	< 0.06	good
	90% CI	[0.048, 0.065]	-	acceptable
	PCLOSE	0.116	> 0.05	good
information guidelines	AIC	490.678	The smaller the better	-
	BIC	714.960	The smaller the better	-
	CAIC	775.960	The smaller the better	-

The model fit indicators are as follows: in the chi-square test, CMIN=368.678 (df=192, P=0.000), but CMIN/DF=1.920 (<3), which is a good fit; in the residual and absolute fit indices, RMR=0.262 (slightly higher than <0.08), GFI=0.899 (close to 0.90), AGFI=0.867 (slightly lower than 0.90), the fit is good and there is parsimony (PGFI=0.682>0.50); the comparative fit indices (NFI=0.944, RFI=0.933, IFI=0.973, TLI=0.967, CFI=0.972) are all far higher than 0.90, indicating a significant fit advantage; the parsimony indices (PRATIO=0.831, PNFI=0.785, PCFI=0.808) are all above 0.90. The results showed that the economic efficiency and explanatory power were good. In the error approximation analysis, RMSEA=0.056 (<0.06, 90% CI [0.048,0.065]) and PCLOSE=0.116>0.05, indicating a good approximate fitting effect. The information criterion index (AIC=490.678, BIC=714.960, CAIC=775.960) was low, indicating a good balance between goodness of fit and complexity.

This structural equation model demonstrated good fit across multiple dimensions. Although the GFI and AGFI were slightly below ideal, and the RMR was high, considering the overall fit indices, the model's structural design is highly reasonable and suitable for subsequent path coefficient analysis and hypothesis testing. This model allows researchers to further interpret and validate the relationships between variables.

Table 9

Regression Weights

			Estimate	S.E.	C.R.	P	Label
AIIA	<---	AIL	.145	.040	3.625	.000	
AIIA	<---	PU	.096	.035	2.743	.006	
AIIA	<---	PEU	.931	.050	18.453	***	
AIIA	<---	PR	-.101	.035	-2.921	.003	
AU	<---	AIIA	.134	.059	2.290	.022	

The results of each path analysis are as follows: AIL→AIIA (coefficient 0.145, P=0.000), higher AI literacy leads to stronger willingness to use, verifying H1; PU→AIIA (coefficient 0.096, P=0.006), the stronger the perceived academic practicality of AI, the higher the willingness to use, supporting H2; PEU→AIIA (coefficient 0.931, P<0.001), ease of use is the key factor affecting willingness to use, verifying H3; PR→AIIA (coefficient -0.101, P=0.003), higher perceived risk leads to lower willingness to use, supporting H4; AIIA→AU (coefficient 0.134, P=0.022), willingness to use positively affects actual behavior, verifying H5.

All hypothesized paths are significant, and the model's theoretical explanatory power is strong. PEU has the greatest impact on user intention, while AIL and PR have positive and negative impacts, respectively. AIIA significantly and positively predicts AU.

4.2 Qualitative results and discussion

The qualitative phase of this study will utilize semi-structured interviews. Purposive sampling will be used to select 12-15 key informants, encompassing subject matter experts, university faculty, and students in AI-enabled educational environments, ensuring a diverse sample with rich experience and perspectives. Selection will be based on the respondents' experience and engagement with AI technology, ensuring professional and representative data. The interviews aim to gain a deeper understanding of their experiences and suggestions for improvement regarding AI-assisted instruction, thereby complementing and explaining the quantitative findings.

4.2.1 Sample situation

The sample of this study includes teachers and students from different backgrounds to ensure the representativeness and diversity of the data. The details are as follows:

Teacher group (12 people): aged 28-55 (average 38 years old), 7 males and 5 females; from various disciplines such as computer science and educational technology, with an average teaching experience of 12 years, all have experience in AI applications; the educational level is master's degree or above, and 25% have doctoral degrees.

The student group (15 people) is comprised of 8 males and 7 females aged 18-24 (covering all undergraduate grades). They come from engineering, liberal arts, and business backgrounds and have all participated in AI-supported multimedia instruction. Most of them have a positive attitude toward AI and are highly receptive.

The sample is well representative in terms of gender, age, subject background, and technical experience, laying the foundation for subsequent analysis. The diverse characteristics help to fully understand the effects and problems of AI teaching applications.

4.2.2 Thematic analysis

Although thematic analysis is a qualitative method, it can be combined with quantitative results in mixed research to enhance explanatory power. Building on quantitative analysis, this study used NVivo to code open-ended questionnaire and interview data, summarizing themes across participants' attitudes, deepening understanding of the quantitative findings, and promoting the integration of theory and practice. Feedback from teachers and students reveals the advantages of AI technology: first, it enriches learning resources (personalized materials, intelligent review plans, etc.), which aligns with the quantitative results showing that perceived ease of use (PEU) positively impacts learning motivation; second, it provides timely feedback (the AI system provides instant error correction, allowing teachers to adjust their teaching using intelligent tools); and third, it enhances interactive teaching (multiple interactive sessions increase engagement, supporting AI's positive impact on learning motivation (AU)).

At the same time, teachers and students mentioned challenges such as technical stability (system crashes, network delays), insufficient data privacy protection, and uneven IT capabilities among teachers. Thematic analysis reveals the mechanisms behind the quantitative data, providing a reference for the application of AI multimedia teaching. This suggests that AI has both advantages and challenges, and that future optimization of instructional design and technical support will require incorporating quantitative results.

4.2.3 Data analysis software (NVivo)

From a teacher's perspective, AI transforms teaching methods (analyzing student data to optimize design and improve classroom relevance) and integrates vast resources, aligning with the quantitative "perceived usefulness" metric. However, AI suffers from technical instability (response delays, poor user interfaces), operational complexity, and a lack of training support (corresponding to the quantitative "perceived risk" metric). Furthermore, AI struggles to grasp students' emotional motivations, requiring further teacher input. From a student's perspective, AI improves the learning experience (rich resources, diverse environments, personalized recommendations to stimulate interest, and immediate feedback to promote independent/collaborative learning), aligning with the quantitative "perceived ease of use" metric. However, some recommendations have low match scores and complex operations, leading to the need for improved interaction and personalization.

In summary, AI can enrich resources, improve feedback efficiency, and foster interaction (validating the quantitative variable path), but technical stability, ease of use, and training support are constraints. Future efforts will require optimization of hardware and software, and enhancement of teacher and student capabilities. Furthermore, teachers' professional judgment and emotional care are irreplaceable. This study, combining quantitative and qualitative data, deepens our understanding of teacher and student experiences and the mechanisms of influence, providing insights for policymaking and instructional improvement.

5 CONCLUSION AND DISCUSSION

5.1 In conclusion

Descriptive statistical analysis of the survey data revealed that university students had a positive attitude toward AI, with high AI literacy scores (foundational skills), above-median perceived usefulness and ease of use (belief in potential efficiency improvements and ease of operation), above-average perceived risk (concerns about privacy and academic integrity), and a positive willingness to use. A SEM analysis based on the TAM, incorporating AI literacy and perceived risk, supported all hypotheses: AI literacy and perceived usefulness/ease of use positively impact adoption intention (consistent with Li et al. and Hu et al., 2025, respectively), perceived risk negatively impacts adoption intention (consistent with Güner and Er, 2025), and willingness to use positively impacts actual behavior (consistent with the TAM and Wang, 2025).Interviews revealed that students believe AI helps boost learning confidence and efficiency (for research and writing assistance), and that its user-friendly interface and timely feedback encourage its use. However, they are concerned about privacy breaches, content accuracy/originality, and academic integrity. It is recommended that schools strengthen AI ethics and risk education to boost adoption.

In summary, this study combines quantitative and qualitative data to explain the drivers and barriers to AI adoption among college students, validates the core ideas of TAM, and provides theoretical and practical insights for educational scenarios.

5.2 Discuss

This study introduces AI literacy and perceived risk variables within the traditional TAM framework to expand the theoretical boundaries of AI education adoption research: AI literacy positively influences adoption intention (consistent with studies in China and abroad such as Zuo, 2024; Li, 2023 and Li et al., 2025, confirming that technical literacy is an important antecedent of AI adoption); verifies the robustness of perceived usefulness and ease of use in AI education scenarios, supporting the core assumptions of TAM and the applicability of emerging technologies; and reveals that perceived risk negatively influences adoption intention (consistent with Güner and Er, 2025, students' concerns about data security and academic integrity reduce adoption intention), supplementing the explanatory power of risk variables in TAM and promoting the development of technology acceptance theory in high-risk situations.

Based on this, this article puts forward the following suggestions from the practical and management perspectives:

First, education departments should integrate AI literacy education into university systems, adopting a phased approach (practicing basic operations in younger grades and strengthening ethics and privacy protection in older grades), and promote cross-disciplinary AI application training. Second, technology developers should optimize AI products for educational scenarios (improving responsiveness, simplifying operation, and optimizing interfaces), and enhance trust in the technology through algorithm transparency and risk warnings. Furthermore, university administrators should establish AI risk prevention and control mechanisms and academic integrity mechanisms (data encryption, content traceability, and misconduct detection), and conduct risk and ethics education. Finally, in terms of industry-university-research collaboration, universities should collaborate with businesses and institutions on projects and competitions, establish innovation laboratories, and provide opportunities for AI practice.

REFERENCES

Anwei. (2024). The path and method of digital technology supporting classroom teaching. China Educational Technology Equipment, (21), 39-41+47.

Dai, X., & Chen, K. (2008). Practice and exploration of bilingual teaching in artificial intelligence. Higher Science Education, (01), 151-153.

Han, J., & Yu, Y. (2010). Research on teaching methods of artificial intelligence courses. Computer Education, (19), 71-73.

Hao, W. (2015). Research on the development trend of multimedia teaching technology. Information and Communication, (02), 151-152.

Li, C., Wang, M., & He, C. (2008). Practice and exploration of "artificial intelligence" teaching based on case teaching. Computer Education, (09), 53-54.

Li, H. (2023). The application of artificial intelligence technology in computer-aided teaching. Shanghai Light Industry, (04), 65-67.

Li, J. (2023). The application of artificial intelligence in vocational education computer course teaching. Integrated Circuit Applications, 40(12), 92-93.

Li, Y., Gui, Q., Wang, B., & Shen, Y. (2008). Optimizing the combination of multimedia teaching methods to improve the quality of diagnosis education. Northwest Medical Education, (03), 573-574.

Lin, M., & Ye, W. (2021). The evolution of classroom teaching environment supported by educational informatization. China Education Technology Equipment, (24), 25-27.

Peng, Y., & Wang, W. (2011). Exploration of teaching methods for intelligent management and decision-making course. Computer Education, (15), 69-71.

Tan, H. (2020). Research on teaching reform of "civil engineering structural testing" course. Jiangsu Science and Technology Information, 37(01), 75-77.

That, W., Zhang, W., Xie, H., & Jin, D. (2024). Research on course design and teaching reform of artificial intelligence neural network technology and its microwave application. Computer Knowledge and Technology, 20(08), 28-31.

Wang, W. (2023). Research on the new mode of information-based teaching of English dialogue class in secondary vocational schools in the context of "Internet plus". China New Communications, 25(21), 224-226.

Wang, X., Wang, Z., & Han, M. (2019). New developments in learning science and instructional design in a technological environment: An interview with Professor Richard Mayer, founder of multimedia learning research. China Electronic Education, (10), 8-13+31.

Yang, J. (2019). The effective application of multimedia technology in junior high school Chinese language teaching. Information Recording Materials, 20(02), 125-126.

Yang, L. (2011). Interest-based teaching method for introduction to artificial intelligence course. Computer Education, (12), 55-58.

Ying, G., & Wang, X. (1999). Issues to be noted in multimedia teaching. Taizhou Teachers' College Press, (06), 41-44+49.

Zhao, Q. (2023). Research on information technology teaching of five-year vocational college mechanical and electrical equipment installation and adjustment training. Agricultural Machinery Use and Maintenance, (11), 139-141+145.

Zhao, X. (2009). Research on the problems of multimedia teaching. Journal of Chifeng University (Natural Science Edition, 25(01), 56-57.

Zhao, Y. (2019). Analysis of piano teaching in the context of intelligent interaction. Art Education, (12), 210-211.

Zhu, Y. (2016). A new teaching model integrating fingertip resource push platform. Journal of Hanshan Normal University, 37(06), 78-82.

Zuo, Y. (2024). Exploration of the implementation of blended teaching mode in higher vocational English with the support of artificial intelligence. Journal of Hubei Open Vocational College, 37(21), 144-146. Chen, F. (2019). Design and implementation of intelligent classroom platform based on artificial intelligence. Modern Electronic Technology, 42(09), 183-186.

Authors' Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

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