MSI Journal of
AI and Technology

Volume: 2, Issue: 3 (July-September 2026)
Published by *MSI Publishers*
ISSN 3107-6181 (Online)

Recived: 24-05-2026
Accapted: 04-07-2026
Published: 07-07-2026

Extending UTAUT to Explain Primary School Teachers' Intention to Use AI Teaching Tools: The Role of I-TPACK Competence

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ABSTRACT: This study investigates the factors influencing primary school teachers' intention to use AI teaching tools in Southwest China. Although AI tools are increasingly used for lesson preparation, instructional material generation, assessment design, classroom activity planning, and feedback support, their availability does not necessarily lead to meaningful pedagogical adoption. Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Intelligent Technological Pedagogical Content Knowledge (I-TPACK) framework, this study examines the effects of performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence on teachers' intention to use AI teaching tools. A quantitative survey was conducted among 502 full-time primary school teachers from Sichuan, Yunnan, Guizhou, and Chongqing. Structural equation modeling was performed using SPSS and AMOS. The results indicate that performance expectancy, effort expectancy, facilitating conditions, and I-TPACK competence significantly and positively influenced teachers' intention, whereas

 DOI: ***10.5281/zenodo.21236291***

social influence had no significant direct effect. I-TPACK competence was the strongest predictor. The findings suggest that AI adoption among primary school teachers is driven more by professional competence, perceived instructional value, usability, and concrete support conditions than by external normative pressure. This study extends UTAUT by adding a teacher-specific AI pedagogical competence factor and provides implications for teacher training, school support, and AI teaching-tool design.

Keywords: *AI teaching tools; primary school teachers; UTAUT; I-TPACK competence; behavioral intention; Southwest China*

1. Introduction

Artificial intelligence is increasingly reshaping school education as part of broader educational digital transformation. Recent studies show that AI has been applied across teaching, learning, assessment, and educational administration, and its pedagogical value is most evident when it supports teachers' instructional preparation and classroom decision-making rather than functioning as a stand-alone substitute for teachers (Tan et al., 2025). In daily school teaching, AI-based and large language model-based tools can assist teachers in preparing lesson plans, developing teaching materials, generating exercises, searching and organizing learning resources, summarizing content, designing assessments, supporting differentiated instruction, and preparing feedback for students (Moundridou et al., 2024). In China, generative AI tools such as Doubao, Tencent Yuanbao, Kimi, and DeepSeek have become increasingly visible in teachers' work routines. A recent survey on AI use among primary and secondary school teachers in China reported that AI applications are most commonly used for lesson preparation, lesson-plan writing, PPT production, and teaching-resource retrieval, indicating that AI is becoming a practical auxiliary tool in teachers' daily work (Moschaki et al., 2026). However, the educational value of these tools depends on teachers' professional interpretation and pedagogical adaptation. AI may reduce repetitive workload and provide initial instructional resources, but teachers remain responsible for judging content accuracy, aligning materials with curriculum standards, adapting outputs to students' developmental needs, and making ethical and pedagogical decisions in classroom practice (Kic-Drgas & Kılıçkaya, 2026).

The adoption of AI teaching tools is particularly complex in primary education because

 DOI: ***10.5281/zenodo.21236291***

young learners are still developing basic cognitive, social, and emotional abilities. Therefore, AI use in primary schools must be guided by age-appropriate design, data privacy protection, and human-centered educational principles (Yim & Su, 2025). Teachers need to judge whether AI-generated content is accurate, curriculum-aligned, pedagogically useful, and suitable for students' developmental stages. Thus, AI adoption is not merely a matter of technological access or operational convenience; it also requires teachers' professional capacity to evaluate AI outputs, adapt materials for classroom use, protect student data, and maintain human judgment in teaching (Rana et al., 2024).

Southwest China provides a meaningful context for examining primary school teachers' adoption of AI teaching tools, because educational digitalization in China still shows clear regional and urban-rural differences (Li & Manzari, 2025). Sichuan, Chongqing, Yunnan, and Guizhou include provincial capitals, county-level cities, rural schools, mountainous areas, and remote educational settings, where schools may differ in digital infrastructure, internet connectivity, access to digital resources, teacher training opportunities, and technical support. Recent evidence from China shows that rural teachers tend to have lower ICT attitudes, ICT skills, data literacy, and digital teaching competence than urban teachers (Lin et al., 2023). Similarly, Zhao (2024) confirmed that a new digital divide exists between urban and rural teachers in China, and that differences in the digital environment and digital literacy significantly affect teachers' ICT competence. In primary education, Li (2025) also found that urban primary teachers showed higher TPACK proficiency and more positive attitudes toward technology integration, while rural teachers were constrained by limited resources, access, and professional support. These contextual differences may influence whether teachers perceive AI teaching tools as useful, easy to use, adequately supported by school conditions, and compatible with classroom practice, which are key factors in educators' acceptance of AI tools.

Existing educational technology studies have frequently used the Unified Theory of Acceptance and Use of Technology to explain users' behavioral intention. UTAUT identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as major predictors of technology acceptance (Venkatesh et al., 2003). However, AI-supported teaching requires more than general acceptance. A teacher may believe that AI is useful and easy to operate but still lack the professional competence to evaluate AI-

 DOI: ***10.5281/zenodo.21236291***

generated content, align it with curriculum objectives, or transform it into developmentally appropriate activities. This limitation is particularly important in primary education, where the suitability of instructional content and the ethical use of student-related information require careful professional judgment.

To address this limitation, this study integrates I-TPACK competence into the UTAUT framework. I-TPACK competence refers to teachers' integrated ability to connect AI-related technological knowledge with pedagogical strategies and subject-content knowledge. It includes the ability to select appropriate AI tools, critically evaluate AI-generated materials, adapt outputs to students' learning needs, design AI-supported classroom activities, and use AI in responsible and ethical ways. Therefore, this study aims to examine how performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence influence primary school teachers' intention to use AI teaching tools in Southwest China. It also identifies which factor has the strongest effect on teachers' intention.

Specifically, the study addresses two research objectives:

RO1: To examine the effects of performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence on primary school teachers' intention to use AI teaching tools in Southwest China.

RO2: To determine which of these factors has the strongest effect on primary school teachers' intention to use AI teaching tools in Southwest China.

2. Literature Review

2.1 Theoretical Approach

This study uses UTAUT as the behavioral acceptance backbone and I-TPACK as the professional competence foundation. UTAUT explains teachers' acceptance-related perceptions and support conditions, whereas I-TPACK explains whether teachers possess the professional knowledge needed to translate AI tools into pedagogically meaningful practice. Together, these perspectives support an extended model in which teachers' intention to use AI teaching tools is shaped by perceived usefulness, perceived ease of use, external expectations, facilitating resources, and AI-related pedagogical competence.

 DOI: ***10.5281/zenodo.21236291***

UTAUT was developed to explain information technology acceptance by integrating major technology adoption theories. In this framework, performance expectancy refers to the degree to which individuals believe that using a technology will improve their performance; effort expectancy refers to perceived ease of use; social influence refers to perceived expectations from important others; and facilitating conditions refer to the availability of organizational and technical support (Venkatesh et al., 2003). In the context of this study, these constructs are used to explain whether primary school teachers perceive AI tools as useful for teaching, manageable in operation, socially encouraged, and supported by schools.

The TPACK framework argues that effective technology integration depends on the interaction among technological knowledge, pedagogical knowledge, and content knowledge (Mishra & Koehler, 2006). In AI-supported teaching, the traditional TPACK framework needs to be extended because AI systems are no longer only passive instructional tools; they can generate learning content, support assessment and feedback, analyze educational information, and provide adaptive learning support (Li et al., 2025). I-TPACK therefore emphasizes teachers' ability to understand AI tools, recognize their affordances and limitations, connect AI functions with subject content and pedagogical strategies, and design AI-supported learning experiences (Celik, 2023). In addition, because AI use in education may involve privacy risks, algorithmic bias, transparency problems, accountability issues, and excessive dependence on automated systems, teachers also need ethical knowledge and human-centered judgment when integrating AI into classroom practice (Yan et al., 2025). This perspective is particularly suitable for primary education because teachers must ensure that AI-supported content is suitable for young learners.

This study combines them into a single explanatory framework. UTAUT explains why teachers may intend to use AI tools from the perspective of perceived value, usability, social pressure, and support conditions. I-TPACK explains whether teachers have the competence to integrate AI into teaching in ways that are curriculum-aligned, developmentally appropriate, and ethically responsible. This theoretical integration provides a stronger basis for explaining AI teaching-tool adoption among primary school teachers.

 DOI: ***10.5281/zenodo.21236291***

2.2 Research Hypotheses and Conceptual Model Development

Performance expectancy refers to the extent to which teachers believe that using AI teaching tools can improve their teaching performance, work efficiency, and instructional outcomes. This definition is adapted from the UTAUT model, in which performance expectancy is defined as users' belief that using a technology will help them achieve gains in job performance (Venkatesh et al., 2003). In the context of primary education, it reflects teachers' judgment of whether AI tools can help them prepare lessons more efficiently, generate teaching materials, design exercises, provide feedback, support differentiated instruction, and reduce repetitive workload (Kayıran et al., 2026). Xu et al. (2024) defined performance expectancy as educators' belief that AI tools can improve teaching outcomes and found that it significantly predicted Chinese university educators' behavioral intention to use AI tools in teaching. Similarly, Zhang and Wareewanich (2024) examined preschool teachers' willingness to use generative AI in Jiangsu Province and found that performance expectancy significantly enhanced teachers' willingness to adopt generative AI. Kalawati et al. (2026) also confirmed that teachers' intention to adopt AI tools was positively influenced by performance expectancy, indicating the explanatory value of UTAUT in educational AI adoption. In K-12-related AI education, Ayanwale et al. (2022) showed that perceived usefulness and AI relevance were important factors associated with teachers' readiness and intention to teach AI. Therefore, the following hypothesis is proposed:

H1: Performance expectancy has a positive impact on primary school teachers' intention to use AI teaching tools.

Effort expectancy refers to the degree to which teachers perceive AI teaching tools as easy to learn, understandable, and convenient to use. In this study, it describes primary school teachers' perception that AI tools can be operated without excessive time, cognitive burden, or technical difficulty. Within the UTAUT framework, effort expectancy is considered an important antecedent of behavioral intention because users are more likely to accept a technology when they believe that its operation is clear, manageable, and compatible with their existing work routines (Taiwo & Downe, 2013). This theoretical logic is particularly relevant to primary school teachers, who usually face intensive teaching, classroom management, assessment, and administrative tasks. If AI tools require complex prompting, repeated adjustment, or additional technical learning, teachers may regard them as another

 DOI: ***10.5281/zenodo.21236291***

source of workload rather than as instructional support. Xu et al. (2024) found that effort expectancy was one of the significant predictors of Chinese university educators' behavioral intention to use AI tools and even emerged as the strongest predictor in their model. Yang (2026) also confirmed that teachers' intention to adopt AI tools was positively influenced by effort expectancy, indicating that perceived ease of use remains important in teachers' acceptance of emerging AI technologies. Therefore, when primary school teachers perceive AI teaching tools as easy to learn, simple to operate, and convenient for daily teaching tasks, they are more likely to develop stronger intention to use them. Based on this reasoning, the following hypothesis is proposed:

H2: Effort expectancy has a positive impact on primary school teachers' intention to use AI teaching tools.

Social influence refers to the extent to which teachers perceive that important others expect or encourage them to use AI teaching tools. In the context of primary education, these important others may include school leaders, teaching-research group members, colleagues, parents, students, and educational authorities. According to the UTAUT framework, social influence is an important antecedent of behavioral intention because users' technology adoption is often shaped by perceived social expectations, professional norms, and institutional climate (Venkatesh et al., 2003). This relationship is especially relevant in school settings, where teachers' instructional decisions are embedded in organizational culture, leadership requirements, peer communication, and policy guidance. Taheri et al. (2025) identified institutional support, social influence, and media narratives as important contextual factors affecting educators' AI adoption. In a UTAUT-based study of preschool teachers in Jiangsu Province, Zhang and Wareewanich (2024) found that social influence significantly enhanced teachers' willingness to use generative AI, indicating that encouragement from the surrounding professional environment can strengthen teachers' adoption intention. Based on this reasoning, the following hypothesis is proposed:

H3: Social influence has a positive impact on primary school teachers' intention to use AI teaching tools.

Facilitating conditions refer to teachers' perceptions that adequate organizational, technical,

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and professional resources are available to support their use of AI teaching tools. In the UTAUT framework, facilitating conditions describe the extent to which users believe that relevant infrastructure and support exist for technology use, including technical resources, knowledge support, and organizational assistance (Venkatesh et al., 2003). Wu et al. (2025) found that facilitating conditions significantly enhanced preschool teachers' willingness to use generative AI, indicating that institutional and technical support can strengthen teachers' adoption intention. Chanda et al. (2025) also defined facilitating conditions as the organizational and technical foundations that support educators' AI use, although their study found a stronger effect of facilitating conditions on actual use than on intention. More broadly, Taheri et al. (2025) identified institutional support and resource availability as key infrastructural factors influencing educators' AI adoption. Therefore, the following hypothesis is proposed:

H4: Facilitating conditions have a positive impact on primary school teachers' intention to use AI teaching tools.

I-TPACK competence refers to teachers' integrated professional ability to understand AI technologies, evaluate AI-generated outputs, connect AI tools with pedagogical strategies and subject content, and use AI in ethically responsible ways. Unlike general digital competence, I-TPACK emphasizes that teachers' AI use should be embedded in curriculum goals, instructional design, learner development, and ethical judgment. Celik (2023) argued that teachers need AI-specific technological, pedagogical, content-related, and ethical knowledge to integrate AI-based tools meaningfully into education. In primary education, this competence is particularly important because teachers must judge whether AI-generated materials are accurate, age-appropriate, curriculum-aligned, and suitable for young learners. Yang et al. (2025) integrated UTAUT and TPACK to examine middle school EFL teachers' intention to use AI and found that AI-TPACK had significant positive predictive power on behavioral intention. Kayalı et al. (2026) further showed that AI-TPACK is formed through the interaction of AI-technological knowledge, pedagogical knowledge, content knowledge, and composite knowledge elements, indicating that AI integration requires multidimensional professional knowledge rather than isolated technical skills. Oved and Alt (2025) also found that teachers' intention to use educational AI tools was positively related to their core TPACK factor. Therefore, the following hypothesis is

 DOI: ***10.5281/zenodo.21236291***

proposed:

H5: I-TPACK competence has a positive impact on primary school teachers' intention to use AI teaching tools.

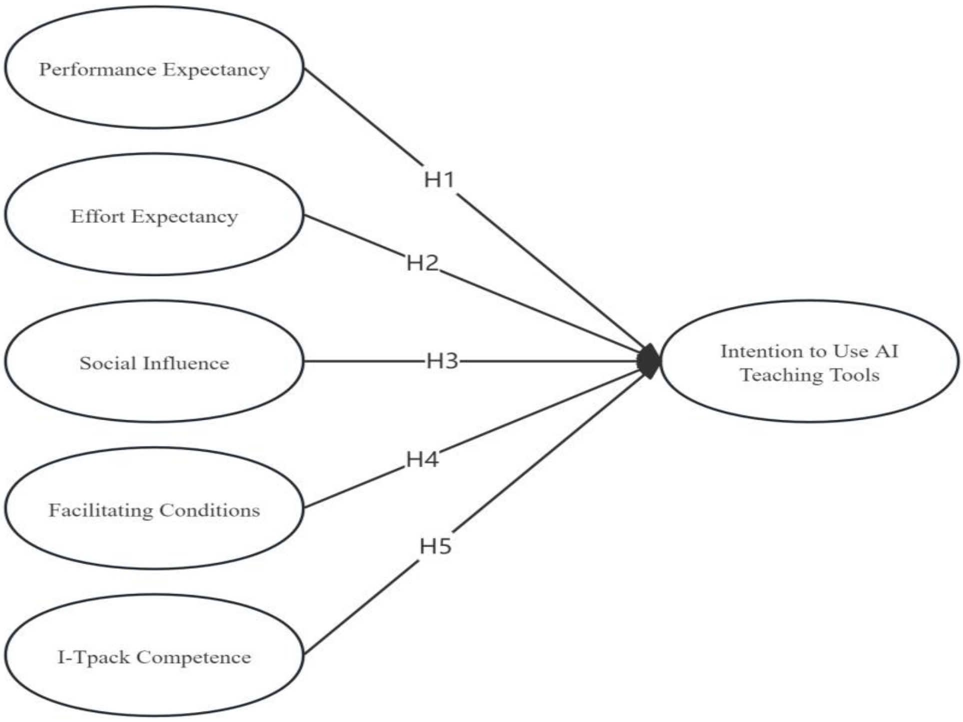

Figure 1. Conceptual model

3. Method

3.1 Data collection

This study employed a quantitative cross-sectional survey design to examine primary school teachers' intention to use AI teaching tools. A survey design was appropriate because the study aimed to collect standardized responses from a relatively large group of teachers and to test the relationships among latent variables through structural equation modeling. The target population was full-time primary school teachers in Southwest China, including Sichuan, Yunnan, Guizhou, and Chongqing. These areas were selected because they include diverse educational settings, ranging from provincial-capital schools to county-level, township, rural, mountainous, and remote schools. The minimum sample size was determined according to the requirements of factor-based and structural equation modeling research. SEM studies require an adequate sample size to ensure stable parameter estimation, sufficient statistical power, and reliable model testing. Wang and

 DOI: *10.5281/zenodo.21236291*

Rhemtulla (2021) emphasized that statistical power in SEM depends on model structure, factor loadings, and target effects, while Wolf et al. (2013) noted that SEM generally requires a sufficiently large sample because model fit, parameter estimation, and standard errors are sensitive to sample size. In this study, the questionnaire contained 21 core measurement items covering performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and intention to use AI teaching tools. Following a conservative respondent-to-item ratio of 20:1, the minimum number of valid responses was calculated as follows: 21 items × 20 respondents = 420 valid responses. Thus, at least 420 valid questionnaires were required for the formal analysis. To allow for incomplete answers, patterned responses, invalid cases, and other data-screening exclusions, a 20% invalid-response rate was considered in the distribution plan. The required number of questionnaires to be distributed was calculated as follows: 420 ÷ (1 − 0.20) = 525 questionnaires.

Data were collected through school contacts, teacher communication groups, and regional education networks. The survey targeted in-service primary school teachers with regular teaching responsibilities. Respondents were screened to ensure that they were full-time primary school teachers from Sichuan, Yunnan, Guizhou, or Chongqing. Intern teachers, non-primary-school teachers, purely administrative staff without teaching responsibilities, and respondents outside the selected regions were excluded. A total of 525 questionnaires were distributed. After data screening, 502 valid responses were retained for final analysis, yielding an effective response rate of 95.62%. The final number of valid responses exceeded the minimum requirement of 420 and was therefore considered adequate for reliability analysis, validity testing, confirmatory factor analysis, and structural equation modeling.

3.2 Measurement Instruments and Scale Development

The questionnaire measured six constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and intention to use AI teaching tools. All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

Performance expectancy refers to teachers' perception that using AI teaching tools can

 DOI: ***10.5281/zenodo.21236291***

improve teaching performance, work efficiency, and students' learning outcomes. This construct was adapted from Venkatesh et al. (2003). In this study, performance expectancy was measured as a unidimensional construct with four items. These items assessed whether AI teaching tools could enhance instructional efficiency, accelerate lesson preparation and assignment grading, increase teaching productivity, and support better teaching performance evaluation.

Effort expectancy refers to teachers' perception of the ease of using AI teaching tools, including interface clarity, learnability, and operational simplicity. This construct was also adapted from Venkatesh et al. (2003). It was measured as a unidimensional construct with four items, covering whether AI teaching tools have a clear and intuitive interface, are easy to master, are generally easy to use, and require minimal effort to learn.

Social influence refers to the extent to which teachers perceive that important others, such as school leaders, colleagues, students, and parents, expect or encourage them to use AI teaching tools. This construct was adapted from the social influence scale of Venkatesh et al. (2003). In this study, it was measured as a unidimensional construct with three items, focusing on recommendations from school administrators and teaching team leaders, the use of AI tools by influential colleagues, and the support provided by school administration.

Facilitating conditions refer to teachers' perception that organizational and technical infrastructure is available to support their use of AI teaching tools. This construct was adapted from (Venkatesh et al., 2003). It was measured as a unidimensional construct with four items, including school-provided hardware equipment, teachers' necessary knowledge and skills, compatibility between AI tools and commonly used teaching software, and the availability of technical support staff when problems occur.

I-TPACK competence refers to teachers' ability to integrate technology, pedagogy, and subject-content knowledge when using AI tools to solve subject-specific teaching problems. In the thesis, this construct was developed based on the TPACK perspective of Mishra and Koehler (2006) and Schmidt-Crawford et al. (2009). It was measured as a unidimensional construct with three items, assessing teachers' ability to select appropriate AI tools according to subject characteristics, integrate AI tools into instructional design,

 DOI: ***10.5281/zenodo.21236291***

and use AI tools to address students' common learning difficulties in specific knowledge areas.

Intention to use AI teaching tools refers to teachers' subjective possibility, plan, or expectation to use AI teaching tools in future teaching. This construct was adapted from Venkatesh et al. (2003). It was measured as a unidimensional construct with three items, including teachers' plan to try or continue using AI teaching tools in the upcoming semester, their expectation of using AI tools more frequently in future teaching, and their plan to use AI teaching tools regularly to support teaching.

Before the formal survey, a pilot test was conducted to examine item clarity, reliability, and preliminary item performance. The corrected item-total correlations of the pilot items ranged from 0.673 to 0.862, indicating satisfactory item discrimination. The Cronbach's alpha coefficients for the six constructs ranged from 0.878 to 0.922, exceeding the commonly accepted threshold of 0.70. Therefore, the questionnaire demonstrated satisfactory internal consistency and was considered suitable for the formal survey.

3.3 Data Analysis

The collected data were analyzed using SPSS and AMOS. First, descriptive statistics were used to summarize the demographic characteristics of the respondents and the general distribution of the main variables. Descriptive analysis is commonly used in quantitative survey research to present frequencies, percentages, means, and standard deviations, thereby providing a basic profile of the sample and an initial understanding of the observed data.

Second, reliability analysis was conducted to assess the internal consistency of the measurement scales. Cronbach's alpha was used to examine whether the items within each construct consistently measured the same latent concept. A Cronbach's alpha value above 0.70 is generally regarded as acceptable in social science research, indicating satisfactory scale reliability (Hussey et al., 2025).

Third, confirmatory factor analysis was performed in AMOS to examine the measurement model. CFA is appropriate when the researcher has developed a theory-based factor structure and needs to test whether the observed items adequately represent their

DOI: ***10.5281/zenodo.21236291***

corresponding latent variables (Mishra, 2016). In this study, CFA was used to evaluate the six-construct measurement model, including performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and intention to use AI teaching tools.

Convergent validity was assessed through standardized factor loadings, composite reliability, and average variance extracted. Standardized factor loadings indicate the strength of the relationship between each item and its latent construct. Composite reliability evaluates the internal consistency of the latent construct, while AVE reflects the proportion of item variance explained by the construct relative to measurement error. Factor loadings above 0.50, CR values above 0.70, and AVE values above 0.50 are commonly considered acceptable indicators of convergent validity (Fornell & Larcker, 1981). Discriminant validity was assessed using the Fornell-Larcker criterion by comparing the square root of AVE with inter-construct correlations. Discriminant validity is supported when the square root of AVE for each construct is greater than its correlations with other constructs.

Fourth, common method bias was examined because all data were collected through a self-reported questionnaire. Harman's single-factor test was used as a preliminary diagnostic procedure to determine whether one general factor accounted for most of the covariance among the measurement items. This test is commonly applied in survey-based behavioral research to assess the potential influence of common method variance (Howard et al., 2024).

Finally, structural equation modeling was used to test the hypothesized relationships among the latent variables. SEM is suitable for this study because it allows the researcher to examine the measurement model and structural relationships among latent constructs while accounting for measurement error (Kline, 2024). The structural model tested the direct effects of performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence on primary school teachers' intention to use AI teaching tools. Model fit was evaluated using commonly reported fit indices, including χ^2/df, CFI, TLI, IFI, RMSEA, and SRMR. Direct effects were assessed using standardized path coefficients, standard errors, critical ratios, and significance values.

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4. Results

4.1 Descriptive Statistical Analysis

Table 1 summarizes the demographic and professional profile of the 502 respondents. Female teachers accounted for 64.14% of the sample, while male teachers accounted for 35.86%. Most respondents were between 26 and 44 years old, and the largest teaching-experience group had 8-15 years of experience. In terms of education, 76.29% held a bachelor's degree. The sample also covered different professional titles, subjects taught, school locations, and school types. Public primary school teachers accounted for 88.84% of the sample, while private primary school teachers accounted for 11.16%. The distribution indicates that the sample included teachers from diverse school contexts in Southwest China.

Table 1 Participant's demographics

Variable	**Category**	**Frequency**	**Percentage**
Gender	Female	322	64.14
	Male	180	35.86
Age	45–54	108	21.51
	26–35	167	33.27
	55 and above	32	6.37
	Under 25	44	8.76
	36–44	151	30.08
Teaching experience	16–25 years	106	21.12
	8–15 years	153	30.48
	0–3 years	71	14.14
	4–7 years	104	20.72
	26 years or more	68	13.55
Highest education	Bachelor's degree	383	76.29
	Junior college	57	11.35
	Master's degree	61	12.15

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	Doctoral degree	1	0.2
Professional title	Level II teacher	163	32.47
	Level I teacher	171	34.06
	Senior teacher	46	9.16
	Level III teacher	71	14.14
	Not yet rated	51	10.16
Subject taught	Chinese	136	27.09
	Science	50	9.96
	English	68	13.55
	Music/PE/Art	81	16.14
	Mathematics	124	24.7
	Information technology	21	4.18
	Other	22	4.38
School location	Provincial capital/municipality urban area	96	19.12
	Prefecture-level city district	117	23.31
	County-level city/county	159	31.67
	Township/rural area	130	25.9
School type	Public primary school	446	88.84
	Private primary school	56	11.16

Table 2 presents the descriptive statistics of the main constructs. The mean values of all constructs were above the midpoint of the five-point scale. Performance expectancy recorded the highest mean value, followed by intention to use AI teaching tools, effort expectancy, I-TPACK competence, facilitating conditions, and social influence. These results suggest that teachers generally perceived AI teaching tools as useful and expressed relatively positive intention to use them. However, the comparatively lower mean scores of facilitating conditions and social influence indicate that support conditions and external expectations were perceived less strongly than the instructional value of AI tools.

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Table 2 Descriptive Statistics

Construct	Number of items	Mean	Average SD
Performance expectancy	4	3.739	0.741
Effort expectancy	4	3.688	0.739
Social influence	3	3.489	0.756
Facilitating conditions	4	3.494	0.725
I-TPACK competence	3	3.613	0.762
Intention to use AI teaching tools	3	3.713	0.763

4.2 Reliability and Validity Analyses

The pilot reliability results showed acceptable internal consistency, with Cronbach's alpha values above 0.878 for all constructs. In the formal confirmatory factor analysis, all standardized factor loadings were significant at $p < 0.001$ and ranged from 0.707 to 0.812. Composite reliability values ranged from 0.826 to 0.851, all exceeding the recommended threshold of 0.700. AVE values ranged from 0.561 to 0.649, all above the recommended value of 0.500. These results indicate that the measurement model demonstrated acceptable convergent validity.

Table 3 Convergent Validity

Construct	Item	Standardized Loading	p-value
PE	PE1	0.76	< 0.001
	PE2	0.787	< 0.001
	PE3	0.765	< 0.001
	PE4	0.755	< 0.001
EE	EE1	0.757	< 0.001
	EE2	0.782	< 0.001
	EE3	0.768	< 0.001
	EE4	0.747	< 0.001
SI	SI1	0.794	< 0.001
	SI2	0.766	< 0.001
	SI3	0.789	< 0.001

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FC	FC1	0.751	< 0.001
	FC2	0.766	< 0.001
	FC3	0.707	< 0.001
	FC4	0.77	< 0.001
I-TPACK	ITPACK1	0.812	< 0.001
	ITPACK2	0.809	< 0.001
	ITPACK3	0.796	< 0.001
INT	INT1	0.784	< 0.001
	INT2	0.811	< 0.001
	INT3	0.801	< 0.001

Table 4 presents the discriminant validity results. The diagonal values represent the square roots of AVE. For each construct, the square root of AVE was greater than its correlations with other constructs. For example, the square root of AVE for I-TPACK competence was 0.806, which was higher than its correlations with performance expectancy, effort expectancy, social influence, facilitating conditions, and intention. Therefore, the six constructs were empirically distinct from one another and suitable for structural equation modeling.

Table 4 Discriminant Validity

Construct	PE	EE	SI	FC	I-TPACK	INT
PE	0.767					
EE	0.287***	0.764				
SI	0.182***	0.213***	0.783			
FC	0.279***	0.273***	0.287***	0.749		
I-TPACK	0.362***	0.341***	0.241***	0.303***	0.806	
INT	0.440***	0.365***	0.170***	0.345***	0.509***	0.799

Note: Diagonal values are the square roots of AVE. *** $p < 0.001$.

4.3 Confirmatory Factor Analysis

Table 5 presents the fit results of the measurement model. The χ^2/df value was 1.849, which was below the recommended threshold of 3.000. CFI, TLI, and IFI were all above 0.900, while RMSEA and SRMR were below 0.080. Overall, the measurement model

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achieved satisfactory fit, indicating that the latent constructs were adequately represented by their observed indicators.

Table 5 Measure Model Fit Metrics

Fit index	Result	Recommended criterion
χ^2	321.684	-
df	174	-
χ^2/df	1.849	< 3.00
CFI	0.967	> 0.90
TLI	0.960	> 0.90
IFI	0.968	> 0.90
RMSEA	0.041	< 0.08
SRMR	0.038	< 0.08

4.4 Structural Equation Modeling

Table 6 presents the direct path testing results. Four of the five hypothesized paths were statistically significant. Performance expectancy had a significant positive effect on intention to use AI teaching tools ($\beta = 0.242$, $t = 6.149$, $p < 0.001$), supporting H1. Effort expectancy also positively affected intention ($\beta = 0.148$, $t = 3.779$, $p < 0.001$), supporting H2. Social influence had no significant effect on intention ($\beta = -0.027$, $t = -0.715$, $p = 0.475$), so H3 was not supported. Facilitating conditions positively influenced intention ($\beta = 0.144$, $t = 3.676$, $p < 0.001$), supporting H4. I-TPACK competence had the strongest positive effect on intention ($\beta = 0.333$, $t = 8.244$, $p < 0.001$), supporting H5. Based on the standardized path coefficients and latent-variable correlations, the model explained approximately 37.5% of the variance in teachers' intention to use AI teaching tools.

Table 6 Structural Equation Model Path Test Result

Hypothesis	Path	Standardized β	S.E.	C.R.	p	Result
H1	PE → INT	0.242	0.039	6.149	< 0.001	Supported
H2	EE→ INT	0.148	0.039	3.779	< 0.001	Supported
H3	SI→ INT	-0.027	0.038	-0.715	0.475	Not supported
H4	FC→ INT	0.144	0.039	3.676	< 0.001	Supported
H5	I-TPACK → INT	0.333	0.040	8.244	< 0.001	Supported

Note: β = standardized estimate; *** $p < 0.001$.

DOI: *10.5281/zenodo.21236291*

5. Discussion

5.1 Key Findings

This study examined the factors influencing primary school teachers' intention to use AI teaching tools in Southwest China. The first research objective was to examine the effects of performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence on teachers' intention to use AI teaching tools. The second research objective was to identify which factor had the strongest influence on teachers' intention. The structural model results showed that performance expectancy, effort expectancy, facilitating conditions, and I-TPACK competence significantly and positively influenced teachers' intention, whereas social influence had no significant effect. Among the significant predictors, I-TPACK competence had the strongest effect, followed by performance expectancy, effort expectancy, and facilitating conditions. These results indicate that primary school teachers' intention to use AI teaching tools is shaped more by professional competence, perceived instructional usefulness, ease of use, and school-level support than by external social pressure.

First, performance expectancy had a significant positive effect on primary school teachers' intention to use AI teaching tools. This finding suggests that teachers are more likely to adopt AI tools when they believe that these tools can improve teaching efficiency, lesson preparation, instructional-material development, assessment design, feedback preparation, and differentiated instruction. This result is consistent with Xu et al. (2024), who found that performance expectancy significantly predicted Chinese university educators' behavioral intention to use AI tools in teaching. It also supports Zhang and Wareewanich (2024)'s study of preschool teachers in Jiangsu Province, which found that performance expectancy significantly enhanced teachers' willingness to use generative AI. Compared with these studies, the present study further confirms that perceived usefulness remains important in primary education, where teachers are especially concerned with whether AI tools can reduce repetitive work and support concrete classroom tasks.

Second, effort expectancy also had a significant positive effect on teachers' intention to use AI teaching tools. This finding indicates that primary school teachers are more willing to adopt AI tools when they perceive them as easy to learn, clear to operate, and convenient to integrate into daily teaching. This result is consistent with Xu et al. (2024), who found that

 DOI: *10.5281/zenodo.21236291*

effort expectancy was one of the significant predictors of educators' behavioral intention to use AI tools and even emerged as the strongest predictor in their model. However, it differs from An et al. (2023), whose study of middle school EFL teachers found that effort expectancy did not directly predict behavioral intention but worked indirectly through performance expectancy. This difference may be related to the primary school context in Southwest China. Primary school teachers often face heavy teaching, class management, and administrative responsibilities, so they may be more sensitive to whether AI tools are easy to operate and whether they increase or reduce workload. Therefore, ease of use is not only a technical concern, but also a practical condition affecting teachers' willingness to try AI tools.

Third, facilitating conditions significantly and positively influenced teachers' intention to use AI teaching tools. This result means that teachers are more likely to adopt AI tools when schools provide sufficient digital devices, stable internet access, available AI platforms, technical assistance, professional training, and clear institutional guidance. This finding is consistent with Zhang and Wareewanich (2024), who found that facilitating conditions significantly strengthened preschool teachers' willingness to use generative AI. It also corresponds with Taheri et al. (2025), who reviewed 45 peer-reviewed studies from 2020 to 2024 and identified institutional support and resource-related conditions as important factors influencing educators' AI adoption. In the present study, this finding is particularly meaningful because Southwest China includes urban, county-level, rural, mountainous, and remote schools with different levels of digital infrastructure and teacher support. Even when teachers recognize the value of AI, their adoption intention may remain limited if schools lack technical support, training opportunities, or clear AI-use guidelines.

Fourth, I-TPACK competence had the strongest positive effect on teachers' intention to use AI teaching tools. This is the most important finding of the study. It indicates that teachers' willingness to adopt AI depends most strongly on whether they possess the professional competence to connect AI tools with pedagogy, subject content, curriculum goals, and student learning needs. This finding is consistent with Celik (2023), who argued that AI integration requires teachers to combine technological, pedagogical, content-related, and ethical knowledge rather than relying on technical operation alone. It also supports An et

DOI: *10.5281/zenodo.21236291*

al. (2023), who found that AI-TPACK was an important factor associated with teachers' behavioral intention to use AI in middle school English teaching. Compared with previous studies, the present study further demonstrates that professional competence may be even more important in primary education, because teachers must judge whether AI-generated materials are accurate, age-appropriate, curriculum-aligned, and pedagogically meaningful for younger learners. Therefore, AI adoption in primary schools is not simply a matter of accepting a new technology; it is closely related to teachers' ability to transform AI-generated outputs into responsible and meaningful teaching resources.

Fifth, social influence did not significantly affect teachers' intention to use AI teaching tools, so H3 was not supported. This finding differs from Zhang and Wareewanich (2024), who found that social influence significantly enhanced preschool teachers' willingness to use generative AI. It also differs from Hazzan-Bishara et al. (2025), who reported that teachers' intention to adopt AI tools was positively influenced by social influence. However, the finding is consistent with Xu et al. (2024), who found that social influence did not influence university educators' behavioral intention to use AI tools. AI use in primary education involves strong professional judgment and responsibility. Teachers may not decide to use AI simply because school leaders, colleagues, parents, or educational authorities encourage them to do so. Instead, they may first consider whether AI tools are useful, easy to operate, supported by school conditions, and compatible with their own pedagogical competence. Another explanation is that AI-related norms in primary schools are still developing. Since many schools have not yet established stable policies, shared standards, or mature peer practices for AI use, social pressure may not be strong enough to directly shape teachers' intention.

Overall, the findings directly respond to the two research objectives. Regarding the first objective, this study confirms that performance expectancy, effort expectancy, facilitating conditions, and I-TPACK competence significantly promote primary school teachers' intention to use AI teaching tools, while social influence does not directly affect intention. Regarding the second objective, I-TPACK competence is identified as the strongest predictor. This means that primary school teachers' AI adoption in Southwest China should be understood as a competence-centered process. Teachers are more likely to develop intention to use AI tools when they perceive instructional benefits, find the tools easy to

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use, receive school-level support, and, most importantly, possess the professional ability to integrate AI with pedagogy and subject content..

5.2 Theoretical Contributions

This study offers three main theoretical contributions to research on teachers' AI adoption and educational technology acceptance.

First, this study extends AI technology acceptance research to the context of in-service primary school teachers in Southwest China. Recent studies have examined educators' AI acceptance in different educational settings, such as university educators' intention to use AI tools, preschool teachers' willingness to use generative AI, middle school English teachers' intention to use AI, and teachers' readiness to teach AI in schools (Runge et al., 2025). However, these studies have paid relatively less attention to in-service primary school teachers, especially those working in regions with uneven digital infrastructure and school support. The present study contributes by showing that AI adoption among primary school teachers is not only influenced by general acceptance factors, but also shaped by the specific requirements of primary education, including age-appropriate content, curriculum alignment, classroom guidance, and teachers' professional responsibility for younger learners. In this sense, the study broadens the application boundary of AI acceptance research from higher education, preschool education, and secondary education to the primary school context in Southwest China.

Second, this study enriches the UTAUT-based explanation of AI adoption by integrating I-TPACK competence into the model. Previous UTAUT-based studies have mainly explained AI adoption through performance expectancy, effort expectancy, social influence, and facilitating conditions. Xu et al. (2024) found that performance expectancy and effort expectancy significantly predicted Chinese university educators' intention to use AI tools, while Zhang and Wareewanich (2024) found that performance expectancy, social influence, and facilitating conditions were significant predictors of preschool teachers' willingness to use generative AI. Compared with these studies, the present research demonstrates that I-TPACK competence has the strongest effect on primary school teachers' intention to use AI teaching tools. This finding supports Celik (2023)'s argument that AI integration requires teachers to combine AI-related technological knowledge,

 DOI: ***10.5281/zenodo.21236291***

pedagogical knowledge, content knowledge, and ethical knowledge. It also corresponds with Runge et al. (2025), who showed that AI-related TPACK is important in explaining teachers' behavioral intention to use AI. Therefore, the theoretical contribution of this study lies in showing that teachers' AI adoption should not be explained only through general technology acceptance beliefs. In AI-supported primary education, teachers' professional competence to evaluate, adapt, and pedagogically transform AI-generated outputs becomes a central theoretical factor.

Third, this study clarifies the theoretical boundary of social influence in teachers' AI adoption. Some recent studies have found that social influence significantly affects teachers' willingness or intention to use AI. Zhang and Wareewanich (2024) found that social influence significantly enhanced preschool teachers' willingness to use generative AI, and Taheri et al. (2025) identified social influence as one contextual factor affecting educators' AI adoption. However, the present study found that social influence did not significantly predict primary school teachers' intention to use AI teaching tools. This finding is consistent with Xu et al. (2024), who also found that social influence did not significantly influence university educators' intention to use AI tools. Theoretically, this result suggests that social influence may not always function as a direct predictor in AI adoption models. In primary education, AI use involves professional judgment about content accuracy, children' s developmental appropriateness, privacy protection, and classroom responsibility. Therefore, teachers may rely more on their own competence, perceived usefulness, ease of use, and actual school support than on external expectations from leaders, colleagues, parents, or policy discourse. This contributes to UTAUT by showing that the effect of social influence may be context-dependent and may weaken when technology use requires strong professional autonomy and ethical judgment.

Overall, this study contributes to theory by proposing a competence-centered explanation of primary school teachers' AI adoption. Recent reviews have emphasized that educators' AI adoption is shaped by multiple factors, including pedagogical beliefs, institutional support, resource conditions, and professional development opportunities (Tan et al., 2025). The present study advances this discussion by empirically demonstrating that I-TPACK competence is more influential than the traditional UTAUT predictors in the primary school context. Therefore, the study suggests that future AI adoption models in

 DOI: ***10.5281/zenodo.21236291***

education should move beyond a general usefulness-ease-support logic and give greater theoretical attention to teachers' AI-related pedagogical competence, curriculum judgment, and ethical responsibility.

5.3 Practical Implications

The findings provide practical implications for teacher training, school management, AI teaching-tool development, and regional educational policy. Since I-TPACK competence had the strongest effect on teachers' intention to use AI teaching tools, while performance expectancy, effort expectancy, and facilitating conditions were also significant, practical efforts should focus less on simply encouraging teachers to use AI and more on helping them use AI in pedagogically meaningful, manageable, and well-supported ways.

First, teacher professional development should shift from basic tool operation to I-TPACK-oriented training. Schools and training institutions should not only teach teachers how to open an AI platform, enter prompts, or generate lesson materials. Training should include four practical modules: how to select appropriate AI tools for different subjects, how to evaluate the accuracy and suitability of AI-generated content, how to revise AI outputs according to curriculum standards and pupils' developmental levels, and how to design AI-supported classroom activities. For example, Chinese teachers can be trained to use AI to generate reading questions and then revise them according to students' comprehension levels; mathematics teachers can use AI to design differentiated exercises but must check logical accuracy and difficulty; English teachers can use AI for dialogue practice and feedback, while ensuring that language input is age-appropriate. Such training can help teachers move from "using AI" to "teaching with AI professionally."

Second, schools should provide concrete support conditions rather than only policy slogans. The significant effect of facilitating conditions shows that teachers' willingness to use AI depends on whether AI use is practically feasible in their daily work. Primary schools should provide stable internet access, available devices, approved AI platforms, shared accounts if necessary, and clear technical support channels. Each school can appoint one or two AI support teachers or IT staff to help solve problems related to login, platform use, data security, and classroom application. Schools should also create shared resource banks where teachers can upload effective prompts, revised lesson plans, AI-generated

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worksheets, feedback templates, and classroom examples. This can reduce repeated individual exploration and make AI adoption more sustainable.

Third, AI-related school management should avoid excessive administrative pressure. Since social influence did not significantly affect teachers' intention, simply requiring teachers to use AI, organizing formal campaigns, or treating AI use as a performance indicator may not be effective. Instead, school leaders should create low-pressure experimental spaces. For example, teachers can first be encouraged to use AI in one teaching task per week, such as preparing examples, designing homework, or generating feedback comments. Teaching-research groups can then discuss which AI outputs were useful, which were inaccurate, and how they were revised. This approach is more realistic than forcing all teachers to use AI frequently before they have sufficient confidence and competence.

Fourth, AI teaching-tool developers should design products around primary school teaching needs. The significant effects of performance expectancy and effort expectancy show that teachers care about both usefulness and ease of use. Therefore, AI tools for primary schools should include simple interfaces, ready-to-use subject templates, curriculum-aligned lesson-plan structures, age-appropriate language options, editable worksheets, differentiated exercise generation, and automatic reminders to verify factual accuracy. Developers should also add privacy protection settings, warning messages for uncertain content, and teacher-review functions. AI tools should not present generated materials as final answers; instead, they should position outputs as drafts that teachers can check, revise, and adapt.

Fifth, regional education authorities in Southwest China should provide differentiated support. Sichuan, Chongqing, Yunnan, and Guizhou include urban, county-level, rural, mountainous, and remote schools with different levels of digital infrastructure and teacher training resources. A uniform AI policy may not meet the needs of all schools. Urban schools may focus on advanced AI-supported lesson design and interdisciplinary teaching, while rural and remote schools may first need basic infrastructure, stable internet access, device support, and beginner-level training. County-level teacher-development centers can build regional AI teaching communities, organize online workshops, and provide model lesson cases for less-resourced schools. School-university cooperation can also be used to

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support rural teachers through mentoring, demonstration lessons, and practical AI teaching projects.

Overall, the practical implication of this study is that AI adoption in primary education should be competence-centered and context-sensitive. Teachers are more likely to use AI teaching tools when they can see clear teaching value, operate the tools easily, receive concrete school support, and develop the professional ability to integrate AI with pedagogy and subject content. Therefore, the priority should not be to push teachers to use AI quickly, but to help them use AI safely, selectively, and pedagogically..

5.4 Limitations and Future Research

This study has several limitations that provide directions for future research. First, the study used a cross-sectional survey design. The data reflect teachers' perceptions and intentions at a single point in time, so the findings cannot fully capture how teachers' AI adoption intention changes as they gain experience. Future research may use longitudinal designs to examine the development of teachers' perceptions, competence, and actual AI use over time.

Second, the study relied on self-reported questionnaire data. Although this method is useful for collecting data from a large sample, it cannot fully reveal how teachers actually use AI tools in classrooms. Self-reported intention may differ from actual behavior because teachers may be constrained by school rules, workload, lack of approved platforms, privacy concerns, or technical problems. Future studies may combine surveys with interviews, classroom observations, platform-use logs, teaching portfolios, or AI-supported lesson plans.

Third, the sample was limited to primary school teachers from Sichuan, Yunnan, Guizhou, and Chongqing. Although Southwest China provides an important context for examining educational digitalization and regional diversity, the findings should be generalized cautiously. Future studies could compare teachers across eastern, central, western, and northeastern China or across primary, secondary, vocational, and higher education settings.

Fourth, this study did not examine differences among teacher groups. The effects of performance expectancy, effort expectancy, facilitating conditions, and I-TPACK

DOI: ***10.5281/zenodo.21236291***

competence may vary by school location, subject taught, teaching experience, age, previous AI training, or frequency of AI tool use. Future research could use multi-group analysis to test whether the adoption mechanism differs across these groups.

Finally, this study examined intention rather than actual use behavior. Behavioral intention is an important proximal indicator of technology adoption, but it does not necessarily lead to sustained classroom use. Future research may extend the model by including actual AI use, continued use intention, AI use frequency, or the quality of AI-supported teaching integration as outcome variables.

6. Conclusion

This study examined the factors influencing primary school teachers' intention to use AI teaching tools in Southwest China by integrating UTAUT with I-TPACK competence. Based on 502 valid responses from full-time primary school teachers, the empirical results show that I-TPACK competence is the strongest predictor of teachers' intention to use AI teaching tools. Performance expectancy, effort expectancy, and facilitating conditions also have significant positive effects, whereas social influence does not have a significant direct effect. These findings indicate that teachers' willingness to use AI teaching tools is shaped more by professional competence, perceived instructional value, usability, and concrete support conditions than by external social pressure. Theoretically, the study extends UTAUT by incorporating a teacher-specific AI pedagogical competence factor and demonstrates the importance of linking technology acceptance with professional teaching knowledge. Practically, the findings suggest that AI adoption in primary education should be supported through I-TPACK-oriented teacher training, school-level resources, easy-to-use AI tool design, and differentiated regional policy. Overall, meaningful AI adoption in primary education depends not only on the availability of tools, but also on whether teachers are professionally prepared and institutionally supported to transform AI-generated outputs into accurate, curriculum-aligned, developmentally appropriate, and ethically responsible teaching practices.

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