

FACTORS INFLUENCING PRIMARY SCHOOL TEACHERS' INTENTION TO USE AI TEACHING TOOLS: A CASE STUDY OF SOUTHWEST CHINA

Shi Pu

An Independent Study submitted in partial fulfillment of the Requirements for the Degree of Master of Management Program in Creative Industries Management
Rattanakosin International College of Creative Entrepreneurship
Rajamangala University of Technology Rattanakosin
Academic Year 2026
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ABSTRACT

The objectives of this study were (1) 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, (2) to determine which factor has the strongest influence on primary school teachers' intention to use AI teaching tools, and (3) To examine differences in primary school teachers' intention to use AI teaching tools in Southwest China according to gender, age, and school location.

This quantitative study employed a cross-sectional survey research design. The respondents consisted of 502 full-time primary school teachers from Sichuan, Yunnan, Guizhou, and Chongqing in Southwest China. The respondents were selected using purposive sampling. Data were collected through a structured questionnaire measuring performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and intention to use AI teaching tools. Descriptive statistics, reliability analysis, confirmatory factor analysis, structural equation modeling, an independent-samples t-test, and one-way analysis of variance were used to analyze the data.

The major findings were as follows. (1) Four predictors, including performance expectancy, effort expectancy, facilitating conditions, and I-TPACK competence, had significant positive effects on teachers' intention to use AI teaching tools, indicating that teachers are more likely to adopt AI tools when they perceive them as useful, easy to use, supported by adequate resources, and aligned with their professional competence. In contrast, social influence showed no significant effect, indicating that external expectations from colleagues, school leaders, or society do not directly shape teachers' intention to use AI teaching tools; (2) I-TPACK competence had the strongest influence, indicating that teachers' professional ability to integrate AI with pedagogy and content is the key factor shaping their intention; and (3) No significant difference between gender was identified, whereas statistically significant but small differences were found according to age and school location. Teachers aged 26–35 reported stronger intention than those aged 55 and above, while teachers working in provincial capitals or municipality urban areas reported stronger intention than those working in township or rural schools. Overall, teachers' intention to use AI teaching tools was shaped primarily by professional competence, perceived instructional value, ease of use, and facilitating conditions, while demographic and contextual differences played comparatively limited roles.

Keywords: AI teaching tools, Primary school teachers, UTAUT, I-TPACK competence, Behavioral intention

Advisor's Signature……..

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Table of Contents

Page

Abstract ..... (1)
Acknowledgements ..... (2)
Table of Contents ..... (3)
List of Tables ..... (6)
List of Figures ..... (8)
Chapter 1 Introduction 1
1.1 Background of the Study 1
1.1.1 Research Gap Identification 6
1.2 Significance of the Study 9
1.2.1 Theoretical Significance 9
1.2.2 Practical Significance 10
1.3 Statement of Research Questions 12
1.4 Statement of Research Objectives 12
1.5 Conclusion 13
Chapter 2 Literature Review 14
2.1 Research Background 14
2.1.1 Characteristics of Primary Education Context 14
2.1.2 Application of Artificial Intelligence in Primary Education 15
2.1.3 Current Status of Educational Informatization in Southwest China 16
2.2 Theoretical Basis 18
2.2.1 Unified Theory of Technology Acceptance and Use (UTAUT) 18
2.2.2 Intelligent Technology-Teaching Method-Content Knowledge Framework (I-TPACK) 21
2.3 Conceptual Review 23
2.3.1 Performance Expectancy 23
2.3.2 Effort Expectancy 23
2.3.3 Social Influence 24
2.3.4 Facilitating Conditions 24

Table of Contents (Continued)

Page

2.3.5 I-TPACK Competence 25
2.3.6 Intention to Use Al Teaching Tools 27
2.4 Hypothesis Development 29
2.5 Theoretical Framework 31
2.6 Conclusion 32
Chapter 3 Methodology 33
3.1 Research Tools 33
3.1.1 Operational Definition of Variables 33
3.1.2 Variable Measurement 34
3.2 Data Collection Management 37
3.2.1 Target Population 37
3.2.2 Sampling Techniques 38
3.2.3 Sample Size 39
3.2.4 Data Collection Techniques 39
3.3 Data Analysis 40
3.3.1 Pilot study 40
3.3.2 Descriptive Statistical Analysis 43
3.3.3 Reliability Analysis 44
3.3.4 Confirmatory Factor Analysis 44
3.3.5 Structural Equation Modeling 45
3.3.6 Group Difference Analysis 46
3.4 Conclusion 46
Chapter 4 Results 47
4.1 Descriptive Analysis 47
4.1.1 Sample characteristics 47
4.1.2 Descriptive statistics 49
4.2 Confirmatory Factor Analysis 50
4.2.1 Measurement model and fit metrics 50
4.2.2 Convergent validity 51

Table of Contents (Continued)

Page

4.2.3 Discriminant validity 52
4.3 Structural model path analysis 53
4.4 Group Difference Analysis 54
4.5 Conclusion 55
Chapter 5 Discussion and Conclusion 56
5.1 Implication to Theories 61
5.2 Implication to Practitioners 63
5.3 Limitations of the Study and Implications for Future Research 65
5.4 Conclusion 67
Bibliography 69
Appendixes 76
Appendix A Questionnaire 77
Appendix B Article 87
Curriculum Vitae 120

List of Tables

Table **Page**

Table 2. 1 Key Events in AI Education Policy Adoption by Teachers in Primary Schools in Southwest China 17
Table 3. 1 Summary of Operational Definitions of Core Concepts 33
Table 3. 2 Performance Expectancy Measurement Scale 34
Table 3. 3 Effort Expectancy Scale 35
Table 3. 4 Social influence Measurement Scale 35
Table 3. 5 Facilitating Conditions Scale 36
Table 3. 6 I-TPACK competence Measurement Scale 36
Table 3. 7 Measurement Scale of Intention to Use AI Teaching Tools 37
Table 3. 8 Item analysis for pilot test 42
Table 3. 9 Pretest Reliability Statistics 43
Table 3. 10 Pre-investigation KMO and Bartlett's test 43
Table 4. 1 Sample Information 48
Table 4. 2 Descriptive Statistics Results 50
Table 4. 3 Measure model fit metrics 51
Table 4. 4 Convergence Validity 51
Table 4. 5 Discriminant validity test 53
Table 4. 6 Path effects 54
Table 4. 7 Group Differences in Intention to Use AI Teaching Tools 55

Appendix Table

A. 1 Part 2: Performance Expectancy (PE) 80
A. 2 Part 3: Effort Expectancy (EE) 80
A. 3 Part IV: Social influence (SI) 80
A. 4 Part V: Facilitating Conditions (FC) 80
A. 5 Part VI: I-TPACK Competencies (TPACK) 81
A. 6 Part VII: Intention to Use AI Teaching Tools (INT) 81

Appendix Table (Continued)

Page

B.1 第二部分：绩效预期（PE）.....84
B.2 第三部分：努力预期（EE）.....84
B.3 第四部分：社会影响（SI）.....85
B.4 第五部分：促进条件（FC）.....85
B.5 第六部分：I- TPACK 能力（TPACK）.....85
B.6 第七部分：使用人工智能教学工具（INT）的意图.....86

List of Figures

Figures **Page**

Figure 2. 1 The original model of Planned Behavior Theory (UTAUT) 20
Figure 2. 2 Extended UTAUT theoretical framework of this study.....32

CHAPTER 1
INTRODUCTION

This chapter establishes why the intention of primary school teachers in Southwest China to adopt AI teaching tools warrants investigation. As AI becomes more embedded in teaching and learning, effective use depends not only on access to the technology but also on teachers' willingness and professional capacity to employ it appropriately. The study therefore integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) with I-TPACK competence and considers performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence as antecedents of teachers' intention to use AI teaching tools. The chapter also introduces the research context, explains the significance and research gap, and presents the questions and objectives that guide the study.

1.1 Background of the Study

Artificial intelligence (AI) is increasingly reshaping educational practice and the ways in which learning activities are designed and delivered (Bahroun et al., 2023). The rapid development of generative AI has widened the range of tasks that can be supported, including lesson preparation, production of teaching materials, assessment design, learning analysis, differentiated instruction, and feedback generation (Celik, 2023). In China, large-language-model platforms such as Doubao, Tencent Yuanbao, Kimi, and Deep Seek have become readily accessible to educators. Teachers can use these platforms to locate resources, summarize content, prepare exercises, design classroom activities, and support preliminary feedback. Their role is supportive rather than substitutive: professional responsibility remains with the teacher, while AI can reduce routine workload and assist pedagogical decision making. For this reason, teachers' willingness to use AI teaching tools has become an increasingly important issue as such tools move into everyday instructional settings.

Primary education represents a foundational stage for the development of students' core knowledge, learning routines, cognitive skills, social abilities, and digital literacy (Romadhon et al., 2025). Because children at this level are less mature than students in secondary or tertiary education, they typically need more structured guidance, closer monitoring, and instruction suited to their developmental stage (Pandey, 2024). This places an additional responsibility on primary school teachers when AI is used: generated materials must be checked for factual correctness, age suitability, pedagogical relevance, ethical acceptability, and consistency with curriculum expectations (Gamlem et al., 2026). Accordingly, the use of AI in primary classrooms is not merely a matter of adding a new digital application; it requires teachers to exercise continuing professional judgment concerning instructional standards, child development, information credibility, privacy, and ethical practice (Tan et al., 2025).

The educational value of AI is ultimately determined by how teachers translate available digital functions into appropriate classroom practice (Prilop et al., 2025). Access to software and infrastructure alone does not ensure meaningful implementation. Teachers must determine whether an AI application serves a specific learning objective, check the trustworthiness of generated content, and decide how that content should be adapted for instruction (Yu, 2025). They are also responsible for correcting errors, adjusting materials to pupils' needs, protecting personal data, and maintaining purposeful teacher-student interaction. The UNESCO AI Competency Framework for Teachers similarly links responsible use to technical capability, pedagogical knowledge, ethical judgment, human-centred principles, and continuing professional learning (Huynh et al., 2025). These responsibilities are especially important in primary education because younger pupils may be more susceptible to inaccurate or unsuitable content, algorithmic bias, privacy risks, and excessive reliance on automated systems. Accordingly, adoption of AI teaching tools requires professional judgment and competence in addition to technological availability.

International evidence also shows that artificial intelligence is becoming part of teachers' routine professional work. Data reported from the OECD Teaching and Learning International Survey indicate that about one-third of teachers in participating education systems had used AI for work-related purposes, particularly for summarizing information, preparing lessons, and designing instructional activities (Tashtoush et al.,

2024). Nevertheless, wider use does not by itself guarantee educational value. International guidance emphasizes that generative AI is beneficial only when its application is guided by appropriate pedagogy and sustained human oversight (Nguyen et al., 2025). Thus, the educational contribution of AI depends substantially on teachers' ability to scrutinize, revise, and contextualize machine-generated outputs. This requirement is especially important in primary schools, where instructional content must fit pupils' developmental level and cognitive capacities.

Whether teachers intend to use AI teaching tools reflects a combination of individual perceptions, school conditions, and the wider professional environment. AI may be regarded as a way to improve teaching quality and reduce repetitive work, but some teachers may judge the learning costs of unfamiliar systems to be too high relative to the expected benefits. Adoption decisions can also be shaped by messages and expectations from school leaders, colleagues, parents, and education authorities (Morgan et al., 2024). At the same time, teachers differ in their access to digital infrastructure, institutional assistance, professional learning, technical advice, and collegial support. Research has identified performance expectancy, social influence, facilitating conditions, self-efficacy, and AI-related competence as relevant to teachers' adoption intentions (Zhang et al., 2025). In primary education, these factors influence whether AI is viewed as educationally worthwhile, practically feasible, and compatible with teachers' professional readiness.

The relevance of these factors is heightened in Southwest China, covering Sichuan, Chongqing, Yunnan, and Guizhou, because educational conditions and resource provision vary considerably across the region. Highly developed urban schools coexist with county, rural, mountainous, and remote schools that have different levels of digital infrastructure, instructional resources, teacher-development opportunities, and technical assistance (Guo et al., 2020). Research on educational digitalization in China shows that the digital divide extends beyond access to devices; it also includes unequal connectivity, digital capability, opportunities for technology-supported learning, and effective use of digital resources (Shi, 2024). Studies of ICT use in rural Chinese schools likewise emphasize sustained teacher support and professional capacity building as necessary conditions for reducing regional inequality (Wang et al., 2022). Primary school teachers in Southwest China may therefore face very different circumstances when considering AI

adoption. These differences are directly relevant to facilitating conditions and may also shape opportunities to develop AI-related pedagogical competence.

The Unified Theory of Acceptance and Use of Technology (UTAUT) brings together several earlier explanations of technology adoption and identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as major determinants of behavioral intention and use (Venkatesh et al., 2003). In the present study, performance expectancy concerns the extent to which teachers expect AI tools to enhance teaching outcomes or productivity. Effort expectancy captures perceived difficulty or ease in learning and using such tools. Social influence reflects perceived expectations from people or institutions that matter to teachers, including leaders, colleagues, parents, and education authorities. Facilitating conditions refer to the technical, organizational, and professional resources that make implementation possible. Taken together, these dimensions provide a structured way to examine whether teachers see AI as useful, manageable, socially supported, and practically feasible.

Empirical work supports the relevance of these technology-acceptance factors in educational settings. Yan Yan and Jafri (2026) reported that preschool teachers' adoption of generative AI was associated with perceived usefulness, institutional support, and infrastructure readiness. Nurtanto et al. (2025) likewise found positive links between teachers' AI adoption intention and expected performance improvement, ease of use, social influence, computer self-confidence, and innovativeness. These studies indicate that UTAUT provides a useful starting point for explaining educators' responses to emerging technologies. Nevertheless, positive evaluations of a tool do not fully capture the demands of classroom use. In primary education, teachers must also assess whether AI-generated material is accurate, suitable for pupils' developmental level, pedagogically appropriate, and ethically acceptable.

A limitation of applying UTAUT alone is that the framework gives more attention to users' perceptions and surrounding conditions than to the professional knowledge required for pedagogical integration. Knowing how to operate an AI application does not necessarily mean knowing how to teach with it. A teacher may perceive an AI tool as useful and easy to handle but still be unable to verify generated content, redesign activities, adapt material for different developmental stages, or maintain alignment with curriculum objectives. This distinction is particularly important in primary schools,

where AI outputs often need substantial adjustment before they can become age-appropriate explanations, tasks, interactions, or assessments. Consequently, favorable acceptance perceptions are unlikely to translate into high-quality classroom use unless teachers also possess the competence needed to make sound pedagogical decisions.

TPACK addresses this professional dimension by treating technology, pedagogy, and subject content as interdependent areas of teacher knowledge rather than as isolated expertise (Mishra & Koehler, 2006). With the growing educational role of AI, TPACK has been extended into Intelligent-TPACK (I-TPACK) or AI-TPACK. These variants emphasize teachers' understanding of AI systems, evaluation of their instructional consequences, selection of appropriate applications, and responsible integration into teaching (Băiceanu et al., 2025). Research on teacher AI competence further highlights the importance of recognizing both the capabilities and limitations of AI, keeping human oversight in instructional decisions, and addressing privacy, transparency, bias, and accountability concerns (Mishara, 2024). Thus, the adoption of AI in education is better viewed as a matter of both technology acceptance and professional competence.

For the purposes of this research, I-TPACK competence denotes a primary school teacher's integrated capacity to connect AI-related technological understanding with pedagogical approaches and curriculum content. It includes selecting suitable AI applications, appraising generated information critically, planning AI-supported learning tasks, and modifying outputs in response to pupils' developmental characteristics. When platforms such as Doubao, Tencent Yuanbao, Kimi, or DeepSeek are used to prepare lesson plans, materials, classroom activities, or assessment tasks, teachers with stronger I-TPACK competence are better positioned to check accuracy, revise unsuitable wording, maintain curriculum consistency, and judge whether the resulting activity has genuine instructional value.

Integrating I-TPACK with UTAUT allows the study to address two different but complementary aspects of AI adoption. UTAUT explains acceptance through expected usefulness, perceived effort, social expectations, and available support, while I-TPACK represents the professional knowledge needed to turn an accepted technology into appropriate teaching practice. Recent evidence also connects teachers' AI literacy and professional knowledge with their perceptions of AI, confidence in using it, and willingness to employ it in educational activities (Chen, 2026). This combined

perspective is particularly useful in Southwest China, where differences in infrastructure, training provision, and institutional assistance may influence both access to AI tools and teachers' ability to integrate them into instruction.

On this basis, the study evaluates whether performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence are related to primary school teachers' intention to use AI teaching tools in Southwest China. Intention is treated as an important indicator of readiness for later technology use. Bringing together acceptance perceptions, school-level conditions, and professional capability also makes it possible to examine why increased technological access may not, by itself, result in regular or pedagogically meaningful classroom application. The integrated model therefore focuses on the joint contribution of technology acceptance and teacher competence to future AI use in primary education.

1.1.1 Research Gap Identification

The growing presence of AI teaching tools in primary education has not produced equally consistent, sustained, or instructionally sound use across teachers. The practical concern is therefore broader than access itself. What matters is whether teachers are both willing to adopt these tools and sufficiently prepared to integrate them into everyday teaching in a professionally appropriate manner.

Teachers may recognize that AI can save time and support instructional work while still being reluctant to use it. Possible reasons include the effort required to learn an unfamiliar system, doubts about the reliability of generated information, and uncertainty about its appropriateness for young learners. Decisions may also be shaped by school leaders, colleagues, parents, and education authorities. In addition, effective implementation is difficult when schools have unstable internet connections, unsuitable software, limited technical assistance, unclear institutional rules, or insufficient opportunities for sustained professional learning.

This issue is particularly salient in Southwest China, where schools operate under markedly different conditions across metropolitan, county-level, rural, mountainous, and remote locations. Educational digitalization has widened access to technology, yet the digital divide continues to involve inequalities in equipment, connectivity, digital capability, and effective use of online resources. As a result, teachers in different schools do not necessarily have comparable opportunities to become familiar with AI

applications or to obtain the organizational assistance needed for implementation.

The instructional consequences of AI depend heavily on teachers' judgments about the circumstances and purposes for which it should be used. Advanced technology can remain marginal when teachers are not willing to adopt it, while insufficient professional capability can lead to superficial use that is poorly connected with curriculum requirements or pedagogical goals.

The UNESCO framework for teachers' AI competence places responsible use within a broader set of requirements that includes a human-centred orientation, ethical awareness, knowledge of AI, pedagogical capability, and continuing professional growth (Miao & Cukurova, 2024). Examining adoption is therefore relevant not only to efficiency gains but also to the maintenance of instructional quality and the protection of pupils' well-being.

Investment by schools and education authorities in platforms, hardware, and training may yield limited benefits if teachers see little instructional value in AI, regard the tools as difficult to operate, receive weak encouragement from relevant others, or work without adequate implementation support. Identifying the factors associated with behavioral intention is therefore important for determining which aspects of adoption require the greatest practical attention.

Despite the growing importance of this topic, evidence concerning AI-tool adoption among primary school teachers in Southwest China remains incomplete. Much of the existing research has examined university students, higher-education instructors, pre-service teachers, or educators in other countries and regions. Results obtained from these populations cannot automatically be transferred to in-service primary school teachers, whose work with younger children involves distinctive responsibilities for developmental suitability, classroom supervision, and careful evaluation of instructional content.

Another unresolved issue concerns the school conditions surrounding adoption. Much of the existing literature concentrates on perceived usefulness and ease of use, whereas differences in infrastructure, professional-development access, leadership assistance, and technical resources receive less consistent attention. This is an important omission for Southwest China because school environments are highly diverse. Teachers' responses to the same AI tool may differ substantially depending on the reliability of

local technology, the availability of training, administrative support, and opportunities to obtain help from colleagues.

A further theoretical gap concerns the scope of the conventional UTAUT model. UTAUT explains behavioral intention mainly through performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), but these constructs do not directly represent teachers' capacity to connect AI with subject content and pedagogy. Positive technology perceptions therefore cannot be assumed to produce appropriate instructional practice. Even when AI is viewed as useful and easy to operate, teachers may lack the expertise required to verify generated material, select an appropriate tool, redesign an activity, or keep AI-supported instruction consistent with curriculum aims.

Another limitation of prior work is its tendency to examine technology acceptance, teacher competence, and school support in isolation, even though these elements may jointly shape adoption. Access to devices, software, training, and technical assistance may have little instructional effect if teachers do not possess sufficient I-TPACK competence. Conversely, even teachers with strong AI-related pedagogical capability may face barriers when institutional rules are ambiguous, available tools do not fit instructional tasks, or organizational support is weak.

To address these limitations, the present research develops an extended model that links UTAUT with I-TPACK competence. It tests the relationships of performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence with the intention of primary school teachers in Southwest China to use AI teaching tools. Although AI applications are increasingly available in primary schools, evidence remains limited on the reasons teachers in this educationally diverse region choose to adopt or avoid them. In particular, UTAUT-based studies provide only a partial account of AI-related pedagogical competence, the instructional suitability of technology, and school support. Examining these elements within one model is intended to generate evidence relevant to teacher development, tool design, and school support arrangements.

1.2 Significance of the Study

1.2.1 Theoretical Significance

The present study extends research on AI technology acceptance by concentrating on practicing primary school teachers rather than the university students, higher-education staff, and pre-service teachers who have dominated much of the earlier literature. Although previous studies have clarified important aspects of how educational users perceive and respond to AI, their conclusions may not fully represent the realities of primary-school practice. In-service primary teachers work with younger pupils and must give particular attention to the correctness, developmental appropriateness, instructional usefulness, and ethical acceptability of teaching materials. Their adoption decisions therefore depend not only on whether a technology appears beneficial and easy to use, but also on curriculum requirements, classroom-management responsibilities, children's developmental needs, and continuing professional judgment. By examining this underrepresented professional group, the study expands the population context in which AI acceptance is investigated.

UTAUT explains behavioral intention through four broad considerations: the benefits users expect from a technology, the effort they anticipate in using it, the influence of significant others, and the support available for implementation (Venkatesh et al., 2003). These dimensions indicate whether a technology appears worthwhile, manageable, socially encouraged, and institutionally feasible. They do not, however, directly assess the professional expertise required to use AI for teaching. Operational competence with an AI system is different from pedagogical competence. Teachers also need to judge generated outputs, choose suitable applications, align technological functions with curriculum goals, and design AI-supported learning activities that correspond to pupils' needs.

I-TPACK competence is introduced to represent this teacher-specific professional dimension within the technology-acceptance model. Building on TPACK, it views AI-related competence as an integrated use of knowledge about AI, pedagogy, and subject matter (Mishra & Koehler, 2006). When combined with UTAUT, the framework can distinguish between two sources of adoption readiness: acceptance-related perceptions and external conditions on the one hand, and the professional ability to use AI meaningfully in instruction on the other. The resulting model is therefore more

closely tailored to educational practice than a general user-acceptance model alone.

The study also tests this extended framework in the specific setting of primary education in Southwest China. Many technology-acceptance studies have been conducted in environments where infrastructure, digital access, and institutional support are comparatively stable. Conditions in Southwest China are less uniform: urban, county, rural, mountainous, and remote primary schools may differ in internet and device availability, teacher-development opportunities, access to new technologies, administrative assistance, and institutional readiness. This heterogeneity provides a useful context for examining whether the explanatory relationships in the extended UTAUT framework remain applicable when educational conditions vary substantially.

By examining UTAUT variables, I-TPACK competence, and behavioral intention among in-service primary school teachers in Southwest China, the research provides a context-based test of technology-acceptance theory. It considers whether relationships derived from general technology-adoption research remain meaningful in a region where professional support and educational resources are unevenly distributed. The results can therefore indicate whether the effects of acceptance perceptions and professional competence vary with institutional and regional circumstances, helping move technology-adoption research beyond assumptions of uniformity across settings.

1.2.2 Practical Significance

The practical value of the research concerns four areas: teacher development, school support, the design of AI teaching tools, and regional education policy. Examining the relationships between teachers' adoption intention and performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence helps identify where practical intervention may be most useful. The study therefore provides a basis for considering how psychological perceptions, professional capability, organizational provision, and technological design can jointly strengthen readiness for classroom use of AI.

One implication concerns the content of teacher professional development. Training that concentrates only on logging into platforms, generating outputs, or completing isolated technical procedures is unlikely to be sufficient. Programs should also develop I-TPACK competence through subject-specific AI tasks, guided lesson-design practice, evaluation and revision of AI-generated content, discussion of

privacy and ethical responsibilities, and exercises based on authentic classroom situations. Such preparation can help teachers move from basic operational familiarity toward informed pedagogical use and may strengthen their confidence in applying AI within sound instructional practice.

A second implication concerns the working environment created by schools. Teachers' adoption decisions depend partly on whether the organization makes AI use practically workable. Relevant support includes suitable devices, stable connectivity, appropriate software, timely technical assistance, professional-learning opportunities, and explicit institutional guidance. Schools can therefore improve implementation by providing approved tools, reliable networks, accessible consultation, shared teaching resources, and clear rules for responsible use. Allocating time for experimentation and peer exchange can also help teachers discuss implementation problems and refine AI-supported lesson designs, thereby reducing uncertainty in day-to-day use.

A third implication relates to the design of AI teaching tools themselves. For primary school teachers, technical sophistication is less important than whether a tool is useful in real instructional tasks, easy to operate, pedagogically appropriate, reliable, and compatible with classroom routines. In terms of performance expectancy, developers should make benefits visible in activities such as lesson preparation, material creation, formative assessment, differentiated instruction, classroom-task design, and feedback. In terms of effort expectancy, interfaces and procedures should be clear and uncomplicated. Tools intended for primary education should additionally support curriculum alignment, age-appropriate output, easy editing, subject-specific guidance, factual checking, privacy protection, and content-suitability safeguards.

Fourth, the study has implications for regionally differentiated policy in Southwest China. Educational conditions differ substantially among provincial capitals, county-level cities, rural communities, mountainous areas, and remote schools, particularly with respect to digital infrastructure, teacher-development opportunities, technical assistance, access to AI applications, and institutional readiness. A single standardized support model is therefore unlikely to be equally effective everywhere. Education authorities should tailor assistance to local circumstances. Schools with fewer resources may require improvements in connectivity and hardware, dependable access to appropriate AI platforms, and continuing technical services. Regional policy should

simultaneously invest in sustained teacher-capacity building through targeted professional learning, online training provision, interschool teacher communities, school-university partnerships, and dedicated support for teachers in rural and remote settings.

Taken together, the practical implications point to a coordinated approach to AI adoption. I-TPACK competence highlights the need for deeper professional preparation; performance and effort expectancy emphasize tools that deliver clear instructional value without unnecessary complexity; and facilitating conditions draw attention to school resources and technical support. Because educational conditions differ across Southwest China, implementation policies also need to reflect local circumstances rather than assume identical needs across schools.

1.3 Statement of Research Questions

RQ1: How do performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence affect primary school teachers' intention to use AI teaching tools in Southwest China?

RQ2: Which of these factors has the strongest effect on primary school teachers' intention to use AI teaching tools in Southwest China?

RQ3: Does primary school teachers' intention to use AI teaching tools in Southwest China differ according to gender, age, and school location?

1.4 Statement of 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.

RO3: To examine differences in primary school teachers' intention to use AI teaching tools in Southwest China according to gender, age, and school location.

1.5 Conclusion

Chapter 1 established the context and rationale for studying AI teaching-tool adoption among primary school teachers in Southwest China. It argued that meaningful integration depends on teachers' willingness to use AI, their professional capacity to apply it appropriately, and the conditions provided by their schools. These considerations informed the inclusion of performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence in the research framework. The chapter also clarified the study's theoretical and practical significance and set out the research questions and objectives that guide the literature review and hypothesis development in Chapter 2.

CHAPTER 2
LITERATURE REVIEW

Chapter 2 reviews the scholarship needed to position the study of AI teaching-tool adoption among primary school teachers in Southwest China. The review first considers the characteristics of primary education, the emerging uses of AI in school practice, and uneven patterns of educational digitalization across the region. It then introduces UTAUT as the principal acceptance framework and I-TPACK as a complementary perspective on teachers' ability to integrate AI with pedagogy and subject knowledge. The chapter subsequently examines each study construct—performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and intention to use AI teaching tools—and develops five hypotheses from relevant theoretical and empirical work. It closes by presenting the extended framework used in the empirical analysis.

2.1 Research Background

2.1.1 Characteristics of Primary Education Context

The primary-school period, generally covering ages 6–12, is an important stage for the formation of cognitive abilities, learning habits, and social development (Chiu, 2021). Relative to secondary and higher education, primary schooling involves a broader range of learning activities and a stronger need for day-to-day classroom management. Teachers therefore perform multiple roles: besides delivering subject knowledge, they maintain classroom order, safeguard pupils, and serve as a key link between families and schools (Calleja & Camilleri, 2025).

Primary education in China is gradually placing less emphasis on exclusively teacher-directed instruction and more on inquiry-oriented and technology-supported approaches. The increased use of project-based learning and large-unit teaching has consequently raised expectations for teachers' curriculum design and instructional-resource coordination (Zhang et al., 2025). At the same time, many teachers work with large

classes of approximately 40–50 pupils and carry substantial non-instructional duties. AI applications may ease some repetitive tasks, such as marking assignments or recording attendance, thereby freeing time for more pedagogically demanding and creative work. However, tools that are difficult to learn or poorly aligned with established workflows may instead increase cognitive burden and resistance to technology.

Ethical concerns are especially pronounced in primary education because younger pupils may be less able to question the authority of technological outputs and can be vulnerable to treating algorithmic responses as inherently correct. In December 2025, the Nanjing Mechanics Primary Education Group issued China's first Ethical Handbook for AI Use by Primary School Students. The handbook set out 58 guidelines organized around five areas—safety, integrity, civility, critical thinking, and creativity—and included requirements concerning academic honesty and disclosure of AI-assisted work (Jiangsu Network Information, 2025). This development illustrates that primary-school AI education requires more than operational proficiency. Teachers also need the media-literacy and ethical-education capabilities necessary to help pupils question AI outputs, recognize algorithmic bias, and protect personal information. Yet the development of these combined competencies has received insufficient attention in existing research.

2.1.2 Application of Artificial Intelligence in Primary Education

Within primary education, AI applications now extend across instruction, learning support, assessment, and school management. Their use can be summarized into four principal categories:

1. One important application is AI-assisted content generation and lesson preparation. Generative AI platforms, including Wenxin Yiyang, Kimi, and DeepSeek, can help teachers prepare lesson plans, presentation materials, exercises, and supplementary reading resources more efficiently (Zhang et al., 2026). Evidence from county-level primary and secondary schools in China indicates that DeepSeek and Doubao are among the AI tools most frequently used by teachers, particularly for locating teaching resources and supporting curriculum design.

2. Intelligent assessment and grading: OCR and NLP can support automated marking of objective items and assist with scoring and grammar-related feedback for English and Chinese written work (Fokides & Peristeraki, 2025).

3. Virtual experimentation and immersive learning: VR and AR can reproduce situations that are difficult or unsafe to conduct physically, including natural-science experiments and reconstructed historical settings, thereby supporting immersive learning experiences (Chang et al., 2025).

4. Classroom-behavior analysis and decision support: Computer-vision applications can be used to examine indicators such as pupils' attention and emotional states and to provide teachers with visual summaries of overall classroom learning patterns (Liu et al., 2025).

Although the range of available AI applications continues to expand, meaningful alignment between technology and curriculum remains a major implementation challenge (Chiu, 2025). Field evidence from Guangdong, Hainan, Hunan, and other regions indicates that frontline teachers may understand what AI can do while still feeling insufficiently prepared to use it effectively in class; even teachers who have received training may need further technological and pedagogical support. This situation reflects a broader mismatch between tools and teaching practice. On the supply side, many systems prioritize general-purpose functions without close alignment to disciplinary knowledge, teaching methods, or learners' cognitive characteristics. On the professional-development side, insufficiently systematic guidance can leave teachers using technology only at a superficial level.

2.1.3 Current Status of Educational Informatization in Southwest China

Southwest China—comprising Sichuan, Yunnan, Guizhou, and Chongqing—is characterized by complex geography and ethnically diverse communities and has long been an important region for educational development and digital transformation. Recent initiatives, including "New Infrastructure" and "East Data West Computing," have contributed to better internet access and wider provision of multimedia classrooms in primary and secondary schools. Major urban centers such as Chengdu and Chongqing have also developed a growing number of demonstration schools for smart education.

Despite improvements in digital provision, substantial regional inequality remains. Access to and effective application of newer technologies continue to differ between well-resourced urban settings and remote teaching locations. Chen et al. (2025) reported that teachers can remain positive toward intelligent education even when urban-rural disparities in AI infrastructure persist. This suggests that improvements in

attitudes toward AI do not by themselves eliminate structural differences in the conditions under which teachers can use it.

Table 2.1 summarizes major developments in AI-related education policy affecting primary schools in Southwest China between 2017 and 2024 and indicates how these policy changes have influenced teachers' adoption of technological tools.

Table 2. 1 Key Events in AI Education Policy Adoption by Teachers in Primary Schools in Southwest China

Time Nodes	Policy Documents/Events	Core Content	Impact of Teacher AI Tool Usage	Source
July 2017	The State Council's "New Generation Artificial Intelligence Development Plan"	It explicitly proposes to introduce AI-related courses in primary and secondary education.	The national strategic status of AI education has been established, providing a basis for local policy formulation.	the State Council
April 2018	Ministry of Education's "Education Informatization 2.0 Action Plan"	Promote the innovative application of artificial intelligence, big data and other technologies in education and teaching	Teachers are required to enhance their information technology application skills, but the focus has not yet been on specialized AI	ministry of education
May 2019	Chongqing Starts Pilot Project of "Smart Education"	Select 100 primary and secondary schools to carry out AI education pilot, build smart campus	Teachers in pilot schools are the first to access AI teaching tools, forming an early adopter group	Chongqing Municipal Education Commission
March 2020	Sichuan Province's "Guidelines for AI Curriculum in Compulsory Education"	AI literacy courses will be introduced for grades 3-6, requiring teachers to have basic AI literacy.	Clear requirements for teachers' AI knowledge reserves to promote the growth of training demand	Sichuan Provincial Department of Education
July 2021	Double Reduction Policy Fully Implemented	Restricting subject-based training and encouraging the use of technology to improve the quality of classroom teaching	Teachers seek AI tools to achieve "reducing burden and increasing efficiency", and their motivation for using them has changed	General Office of the CPC Central Committee

Table 2. 1 (Continued)

Time Nodes	Policy Documents/Events	Core Content	Impact of Teacher AI Tool Usage	Source
September 2022	Guizhou Province's "AI Education Support Program for Ethnic Regions"	Equipping Schools in Remote Ethnic Areas with AI Teaching Equipment and Teacher Training	Reducing the regional gap, but teachers' technology acceptance becomes a new constraint	Guizhou Provincial Department of Education
June 2023	Yunnan Province's "AI + Quality Education" Integration Project	Promote the integration of AI tools with labor education, aesthetic education and other disciplines	Expanding the Application Scenarios of AI Tools Challenges Teachers' Interdisciplinary Integration Ability	Yunnan Provincial Department of Education
March 2024	Notice of the Ministry of Education on Strengthening Artificial Intelligence Education in Primary and Secondary Schools	Systematically planning the implementation path of AI education in primary and secondary schools, clarifying the objectives for the primary school stage	Provide clear policy guidance and resource support for teachers to use AI teaching tools	ministry of education

As Table 2.1 indicates, the policy emphasis has progressively moved from broad strategic direction toward concrete classroom implementation. At the same time, expectations placed on teachers have evolved from encouraging early experimentation to requiring more explicit competency standards. This shift has increased the pressure on educators in Southwest China, particularly middle-aged and older teachers in rural settings. Because technological change can occur more rapidly than conventional professional-skill development, some teachers may face an ongoing mismatch between the volume of new digital information and the competencies needed to use it effectively.

2.2 Theoretical Basis

2.2.1 Unified Theory of Technology Acceptance and Use (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003) through the integration of eight earlier approaches to technology-related behavior, including the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), and the Technology Acceptance Model (TAM).

In the original validation, UTAUT explained about 70% of the variance in behavioral intention, demonstrating strong explanatory potential for technology acceptance and use. The framework identifies four principal determinants:

Performance Expectancy (PE) represents the extent to which a person expects technology use to improve task performance or work outcomes. Within UTAUT, it is one of the principal antecedents of behavioral intention.

Effort Expectancy (EE) concerns how simple and manageable individuals expect a technological system to be when learning and operating it.

Social Influence (SI) concerns users' perceptions of the expectations and encouragement communicated by individuals whose views matter to them, including colleagues, supervisors, and other relevant stakeholders, when deciding whether to adopt a technology.

Facilitating Conditions (FC) refer to users' judgments about whether the organizational infrastructure, technological resources, and practical support required for technology use are sufficiently in place.

Beyond these core determinants, the original UTAUT model treats Behavioral Intention (BI) and Use Behavior (UB) as key outcome variables. The model further incorporates gender, age, experience, and voluntariness of use as moderating factors that can condition the strength of associations between its core constructs.

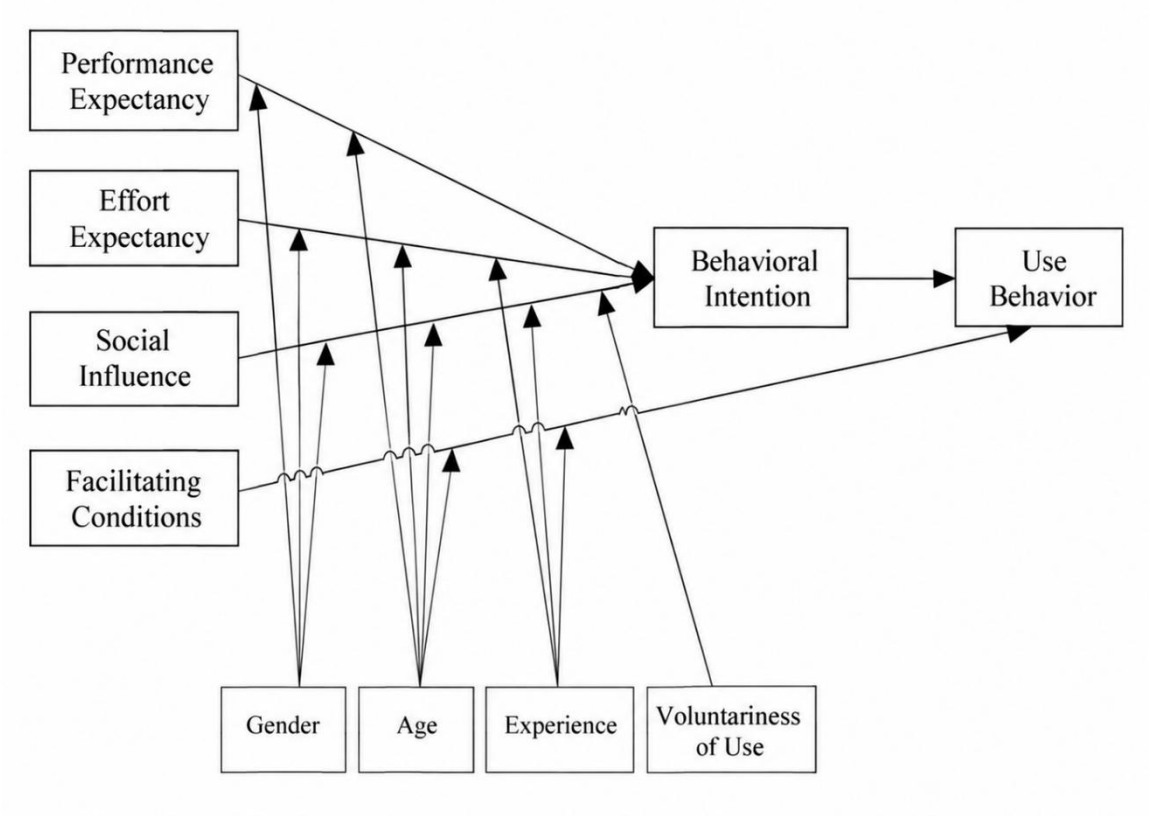


Figure 2. 1 The original model of Planned Behavior Theory (UTAUT)
Source: Venkatesh et al. (2003)

UTAUT serves as the central theoretical framework for three main reasons. First, it combines individual judgments about a technology with the contextual support surrounding its use, allowing adoption to be examined more broadly than through a single-perspective model. In educational technology research, Zhao et al. (2024) found that UTAUT provided stronger explanatory and predictive performance than narrower models such as TAM and TPB. This breadth makes the framework suitable for investigating teachers' decisions about AI teaching tools.

Second, UTAUT has an established measurement structure that has been examined in multiple disciplinary and cultural settings. Evidence from basic education also supports its continued usefulness. Zhao et al. (2025) found that performance expectancy, effort expectancy, and social influence were linked to actual technology use through teachers' behavioral intention, while intention, perceived convenience, and enjoyment also showed direct relationships with use behavior.

Third, UTAUT can accommodate additional antecedent variables when the research setting provides a theoretical reason for doing so. For example, work involving English teachers in county-level primary and secondary schools in China incorporated risk perception as an extension to the original model. Such applications demonstrate that contextual constructs can be added to UTAUT when they address features not sufficiently represented by its original predictors.

2.2.2 Intelligent Technology-Teaching Method-Content Knowledge Framework (I-TPACK)

Mishra and Koehler (2006) introduced Technological Pedagogical Content Knowledge (TPACK) to explain the knowledge teachers require for meaningful technology integration. The framework does not isolate technological knowledge from teaching expertise; instead, it emphasizes the interaction of technology, pedagogy, and subject content within instructional practice.

Generative AI nevertheless introduces characteristics that are not fully captured by the classical TPACK formulation, including greater system autonomy, adaptive interaction, and intertwined social and ethical concerns. Kohnke and Zou (2025) argue that a framework designed primarily for conventional digital technologies does not sufficiently account for issues such as autonomous content generation, real-time AI scaffolding, and algorithmic bias. These developments create a need to reconsider how teachers' professional knowledge is conceptualized in AI-supported education.

Responding to this limitation, Chiu (2025) proposed Intelligent-TPACK, which treats AI literacy together with the practical and ethical competence to use AI as foundational to teachers' work. The framework positions teachers as designers of AI-augmented pedagogy and organizes the required knowledge into five dimensions:

1. AI-Technological Knowledge (AI-TK) concerns teachers' understanding of how AI systems operate, what they are capable of doing, and where their limitations lie. It extends beyond routine digital skills to include purposeful prompting, awareness of data dependence and algorithmic bias, and the ability to assess system reliability, security, and ethical acceptability.

2. AI Content Knowledge (AI-CK): This dimension concerns teachers' capacity to select, verify, and situate AI-generated subject matter appropriately. It includes checking outputs against authoritative information, recognizing possible bias, and adapting generated content to the instructional context.

3. AI-Pedagogical Knowledge (AI-PK) refers to teachers' capacity to design learning experiences in which AI is used in pedagogically purposeful ways. This includes coordinating teacher-AI interaction, redesigning assessment to emphasize higher-order learning, and structuring forms of guided collaboration that support rather than replace students' cognitive engagement.

4. Human-AI Collaborative Knowledge (HAIC-K): This domain concerns the purposeful allocation of cognitive work among teachers, pupils, and AI systems. For instance, AI may handle routine procedures such as grammar correction while teachers devote greater attention to higher-order instructional activities.

5. Ethical Knowledge (Ethic-K) places ethical judgment within the core of I-TPACK. It requires teachers to consider privacy, fairness, transparency, accountability, and related ethical implications when planning and implementing AI-supported instruction.

Celik (2023) further showed that AI-TK functions as a necessary foundation but is not sufficient by itself, whereas AI-PK and AI-CK were the strongest predictors of integrated competence. Ethical knowledge operates across these domains by shaping how AI-related knowledge is applied in educational practice.

I-TPACK is included because adopting AI in primary education involves more than learning how to operate a digital tool; it also requires teachers to reorganize and apply professional knowledge in an AI-rich environment. Stronger I-TPACK competence can help teachers recognize the instructional value of AI, deal more effectively with operational difficulties, and manage ethical concerns. These capabilities can in turn strengthen confidence and willingness to use AI teaching tools.

2.3 Conceptual Review

2.3.1 Performance Expectancy

Performance Expectancy reflects the extent to which users anticipate that a technology will improve the results of their work (Venkatesh et al., 2003). In education, the construct concerns teachers' expectations that AI can enhance instructional performance, reduce the burden of recurring tasks, and contribute to improved student learning.

Scherer et al. (2019) reported that the relationship between Performance Expectancy and technology adoption was notably stronger for teachers than for employees in corporate contexts.

In this study, performance expectancy was represented through four observable aspects: improvement in teaching efficiency, faster lesson preparation and correction, greater work output, and better performance evaluation.

2.3.2 Effort Expectancy

Effort Expectancy concerns the amount of difficulty users anticipate when learning and operating a technology and is closely related to the concept of perceived ease of use in TAM (Venkatesh et al., 2003). The construct is relevant to primary school teachers because age, prior digital experience, and confidence with technology can shape how demanding an AI tool appears. Xu et al. (2024) further showed that perceived ease of use was related to adoption willingness through perceived performance benefits. Their results imply that ease is evaluated together with expected value: teachers are more likely to invest time in learning a tool when the anticipated instructional return justifies that effort.

Conversational interfaces based on large language models have lowered many of the technical barriers associated with AI applications. Yet operational simplicity does not guarantee effective instructional use. Huang and Zhang (2025) noted that teachers who can use AI applications may still lack the professional preparation needed to decide how those applications should be adapted to classroom purposes. This separation between ease of operation and pedagogical capability supports the inclusion of I-TPACK alongside effort expectancy in the present model.

2.3.3 Social Influence

Social Influence refers to perceived expectations, encouragement, or normative pressure from people whose opinions are important to the potential user (Venkatesh et al., 2003). In primary-school settings, these influences can arise from several directions rather than from a single social source.

One source is vertical influence from school administrators and teaching-research leaders. Yang (2026) found that community-related influence was associated with junior teachers' intention to use AI teaching tools, a pattern that may reflect stronger responsiveness to professional and organizational norms among less experienced teachers.

Horizontal social influence originates primarily from colleagues. Jerrim et al. (2025) identified a notable peer effect in technology adoption among county-level teachers, suggesting that the experience of early adopters within the same teaching or research group can reduce uncertainty for colleagues who are still deciding whether to use a technology.

A further source of influence comes from students, reflecting the distinctive interactional setting of primary education. Surveyed teachers reported that pupils' active engagement with AI tools and their questions about these technologies can encourage teachers to learn and experiment with new applications. To represent this pathway, the study broadened the original UTAUT social-influence measurement by including four SI items, one of which captures students' strong interest in and expectations for the use of AI tools during lessons.

2.3.4 Facilitating Conditions

Facilitating Conditions refer to users' perceptions that the organizational arrangements, technical infrastructure, and practical resources necessary for technology use are available (Venkatesh et al., 2003).

Educational infrastructure is unevenly distributed across Southwest China. Better-resourced urban demonstration schools may receive direct technical assistance from technology providers, whereas rural schools may still focus on maintaining dependable internet access and functional computer equipment. Elom et al. (2024) found that resource availability significantly predicts teachers' technology-use behavior, with the relationship becoming especially important where infrastructure is less developed.

For this research, facilitating conditions were represented through three resource categories: physical resources, including hardware and network access; human resources, including technicians and trainers; and institutional resources, such as allocated teaching-research time and incentive policies.

2.3.5 I-TPACK Competence

Technological Pedagogical Content Knowledge (TPACK) describes the intersecting forms of knowledge teachers draw on when technology is used for instruction. Rather than treating technical skill as an independent competence, TPACK focuses on how technological, pedagogical, and subject-matter knowledge are coordinated. Effective technology-supported teaching therefore requires these knowledge areas to be aligned with curriculum objectives, instructional approaches, and the demands of a particular learning context (Mishra & Koehler, 2006).

Technological knowledge concerns teachers' familiarity with digital technologies and their capacity to operate and apply them in practice. Pedagogical knowledge encompasses teachers' understanding of instructional strategies, classroom organization, assessment approaches, and how students learn. Content knowledge represents teachers' command of the disciplinary concepts and subject-specific information they are responsible for teaching. When these three forms of knowledge are integrated, teachers are better positioned to choose suitable technologies, develop instructionally appropriate learning activities, and connect technological use with the intended outcomes of particular subject areas. (Mishra & Koehler, 2006).

Compared with conventional digital technologies, AI systems can produce teaching materials, process learner data, generate feedback, offer recommendations, and adjust responses to user input. At the same time, such outputs may involve factual errors, algorithmic bias, unsuitable content, or insufficient transparency. Teachers therefore need more than basic operational skills; they must also be able to judge the credibility, pedagogical appropriateness, ethical acceptability, and instructional relevance of AI-supported outputs.

Intelligent-TPACK adapts the original TPACK framework to teaching contexts involving artificial intelligence. It focuses on the professional knowledge teachers need to choose AI applications, evaluate their outputs, adapt them to instructional purposes, and use them in an ethically responsible manner (Celik, 2023). More recent conceptual

extensions additionally emphasize AI literacy and AI competence, including knowledge of AI mechanisms, effective human-AI interaction, pedagogical decision making, and responsible technology use (Chiu, 2025).

For this research, I-TPACK competence denotes the integrated capability of primary school teachers to connect knowledge of AI with pedagogical approaches and subject content. It includes understanding the affordances and limitations of AI tools, matching applications to specific teaching purposes, evaluating the accuracy and suitability of generated material, and revising outputs so that they meet curriculum requirements and pupils' learning needs. It also involves designing AI-supported activities and judging whether AI adds genuine instructional value.

This competence requires professional judgment as well as technical familiarity. Teachers need to decide whether a particular AI tool fits the subject, learning objective, activity, and learner group for which it is being considered. Generated content must also be checked for factual correctness, developmental suitability, and consistency with the chosen teaching approach. Such scrutiny is especially necessary in primary education because younger pupils need closer guidance and are less able to independently evaluate AI-produced information.

I-TPACK competence also encompasses teachers' ability to address the ethical responsibilities associated with AI use. This includes awareness of risks involving student privacy, data protection, algorithmic bias, intellectual property, transparency, and overreliance on automated systems. Ethical AI use therefore depends on teachers retaining professional control and ensuring that technology complements, rather than substitutes for, pedagogical judgment and meaningful teacher–student interaction.

I-TPACK competence should not be treated as equivalent to either general digital competence or basic AI literacy. Digital competence is primarily concerned with accessing, operating, producing, and communicating through digital technologies, whereas AI literacy centers on understanding the fundamental principles, capabilities, uses, and societal implications of artificial intelligence.

Basic AI literacy may enable a teacher to operate a generative-AI system and create instructional content, but I-TPACK competence involves a more demanding level of professional judgment. A teacher with stronger I-TPACK competence can determine whether generated material matches curriculum standards, suits pupils' age and cognitive

development, accurately represents subject knowledge, and supports the intended teaching approach. The teacher can then revise the output, embed it within classroom activities, and evaluate its instructional usefulness.

Previous research suggests that teachers' AI-related professional knowledge is associated with their ability to recognize appropriate educational uses, critically examine technology-generated outputs, and respond to risks arising during AI integration (Ning et al., 2024).

The importance of I-TPACK is especially evident in primary schools, where instructional decisions must accommodate pupils' developmental stages, differences in learning needs, curriculum foundations, and patterns of classroom interaction. Effective AI-supported teaching therefore cannot depend on access to digital applications alone. It requires teachers to bring together technological understanding, pedagogical expertise, subject knowledge, ethical awareness, and professional judgment.

I-TPACK competence is positioned in the model as a professional extension to UTAUT. The four UTAUT constructs represent expected benefits, anticipated effort, social influence, and the institutional conditions surrounding AI use. I-TPACK contributes a separate dimension by capturing whether teachers can critically judge, adapt, and apply AI for pedagogical purposes. Its inclusion enables adoption intention to be examined simultaneously from the perspectives of technology acceptance and professional teaching competence.

2.3.6 Intention to Use AI Teaching Tools

Intention to use AI teaching tools refers to teachers' stated readiness and planned willingness to employ AI in future instructional work. It may be expressed through plans to use AI for lesson preparation, teaching-material development, classroom design, assessment, differentiated support, or feedback. Technology-acceptance research commonly treats behavioral intention as a near-term antecedent of use because it represents the stage at which evaluations of a technology are translated into an adoption decision (Davis et al., 1989; Venkatesh et al., 2003). Intention nevertheless remains distinct from actual behavior. A teacher can be willing to use AI but unable to do so because of limited infrastructure, restricted platform access, workload pressures, or institutional requirements.

Teachers are more likely to intend to use AI when they see clear instructional advantages, regard the tools as manageable, perceive their use as acceptable within the professional environment, and believe implementation is feasible at school. Expected advantages can include quicker preparation, stronger instructional support, improved teaching quality, and more responsive provision for diverse learners. Conversely, complicated procedures, high learning demands, and uncertainty about technical operation may discourage adoption. Prior studies have linked performance expectancy, perceived usefulness, effort expectancy, social influence, and facilitating conditions with educators' behavioral intention toward AI-supported technologies (Camilleri, 2024).

Teachers' professional capability constitutes another important basis for the development of behavioral intention. Unlike conventional digital technologies, AI teaching tools are capable of producing, recommending, organizing, and modifying instructional materials. Their use therefore requires teachers to critically judge whether AI-produced content is accurate, suitable for classroom use, and pedagogically appropriate, as well as to consider its consistency with curriculum goals and pupils' developmental needs. I-TPACK competence equips teachers with the expertise to recognize both the instructional potential and constraints of AI, choose applications that fit particular teaching purposes, and coordinate technological resources with pedagogical approaches and subject-specific knowledge. Consequently, teachers with a higher level of AI-related pedagogical competence are more inclined to regard AI as feasible to apply, instructionally relevant, and beneficial to their professional practice.

The dependent variable in this study is teachers' planned willingness to incorporate AI-supported tools into future teaching. This focus is particularly relevant in Southwest China because teachers' opportunities to act on such willingness may differ according to infrastructure, training, technical support, and school readiness. The proposed model therefore relates adoption intention to performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence. In doing so, it examines how personal evaluations, professional capability, social context, and institutional circumstances contribute to primary school teachers' readiness to use AI.

2.4 Hypothesis Development

Performance expectancy is the belief that using a technology will improve work outcomes (Venkatesh et al., 2003). For primary school teachers, expected benefits may include better instructional quality, less time spent on routine administrative or teaching tasks, more efficient lesson preparation, greater responsiveness to learner differences, and faster assessment or feedback. A technology is more likely to be considered for adoption when teachers can connect its advantages directly with the demands of their everyday work.

AI teaching tools can assist with preparing resources, organizing lesson content, interpreting information about student progress, and differentiating learning tasks. If routine work is reduced, teachers may be able to devote more time to professional judgment and interaction with pupils. Studies of educators' adoption of AI and other emerging technologies have consistently linked perceived practical value and expected performance improvement with stronger adoption intention (Nurtanto et al., 2025; Sun et al., 2026). It is therefore reasonable to expect higher intention among primary school teachers who believe AI can improve both instructional quality and work efficiency.

H1: Performance expectancy positively influences primary school teachers' intention to use AI teaching tools.

Effort expectancy captures the perceived ease with which a technological system can be learned and used (Venkatesh et al., 2003). In the present context, it reflects whether primary school teachers view AI teaching tools as understandable, accessible, and convenient in routine work. Tools that integrate smoothly with existing practices and require relatively little extra time, procedural effort, or cognitive burden should be easier for teachers to accept.

The relevance of effort expectancy is particularly evident when teachers have different levels of digital experience and access to technical support. When AI teaching tools involve complicated interfaces, ambiguous instructions, unreliable functions, or substantial learning demands, teachers may hesitate to adopt them despite recognizing their possible instructional value. In contrast, systems that are straightforward to navigate, supported by clear guidance, and simple to operate may lessen uncertainty and increase teachers' confidence in using them. Previous research suggests that perceptions of operational simplicity and the amount of effort required to use a system are associated

with teachers' readiness to adopt AI-supported educational technologies, although the magnitude of this association can differ across educational settings (Nazaretsky et al., 2025). Therefore, this study state:

H2: Effort expectancy positively influences primary school teachers' intention to use AI teaching tools.

Social influence concerns the perceived encouragement, expectations, or pressure that important individuals and groups exert on a person's adoption decision (Korchak et al., 2025). For primary school teachers, these social referents may include school leaders, colleagues, teaching-research groups, parents, education authorities, and professional communities. Their views can affect whether using AI is interpreted as professionally legitimate, institutionally supported, and consistent with prevailing educational expectations.

Technology adoption by teachers takes place within a social and organizational setting. Approval from school leaders can signal that AI use is legitimate, while colleagues who have already used the technology can provide examples and reduce uncertainty. Policy messages and professional expectations may similarly encourage experimentation. In contrast, negative peer attitudes, ambiguous school norms, or concerns from parents can discourage adoption. Taheri et al. (2025) found that social encouragement and pressure can affect teachers' willingness to adopt AI and related educational technologies, particularly when school norms and colleagues' practices shape what is considered acceptable. On this basis, the study proposes:

H3: Social influence positively influences primary school teachers' intention to use AI teaching tools.

Facilitating conditions represent teachers' perceptions that the resources and institutional arrangements required for technology use are sufficiently available (Peñarroja et al., 2019). In this study, they include access to appropriate devices and AI platforms, dependable internet service, responsive technical assistance, relevant professional development, clear school guidance, and enough time for teachers to learn and incorporate AI into their instructional routines.

Perceived usefulness may not lead to adoption when teachers cannot access a tool, obtain help for technical problems, or understand institutional expectations. Conversely, dependable infrastructure, continuing training, leadership assistance, and accessible technical services can reduce implementation barriers and increase perceived control

over use. Research has associated institutional support and adequate technological resources with stronger readiness to adopt technology and with subsequent use decisions (Feng et al., 2025). Accordingly, better facilitating conditions are expected to strengthen primary school teachers' intention to use AI teaching tools.

H4: Facilitating conditions positively influences primary school teachers' intention to use AI teaching tools.

I-TPACK competence is the integrated ability to combine AI-related technological knowledge with pedagogy and subject content (Deb & Sofal, 2026). Teachers with stronger competence in this area can more accurately judge the educational advantages and limitations of AI, choose appropriate applications, adapt generated material for pupils' developmental needs, and respond to concerns involving accuracy, privacy, bias, or overreliance on technology. These abilities can lower uncertainty and strengthen confidence in classroom integration. Teachers with weaker I-TPACK competence, by comparison, may avoid AI, confine it to simple tasks, or remain unsure whether its use is pedagogically appropriate.

Prior research links teachers' AI-related professional knowledge, AI literacy, and technology-integration competence with how they evaluate and intend to use AI-supported teaching (Kayıran et al., 2026). Because primary education requires particularly careful judgment about content suitability and young learners' developmental needs, I-TPACK competence is expected to play an important role in adoption intention. Therefore, this study proposes:

H5: I-TPACK competence positively influences primary school teachers' intention to use AI teaching tools.

2.5 Theoretical Framework

The theoretical model extends UTAUT with I-TPACK to explain primary school teachers' intention to adopt AI teaching tools in Southwest China. Five explanatory variables are examined: performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence. I-TPACK competence is represented by three dimensions—Subject-Specific AI Tool Selection Competence, AI-Integrated Instructional Design Competence, and AI-Supported Learning Problem-Solving Competence. Their relationships with teachers' adoption intention form the core of the

model. Gender, age, and school location are included as control variables to account for possible demographic or contextual variation in the estimates; they are not treated as primary hypothesized predictors.

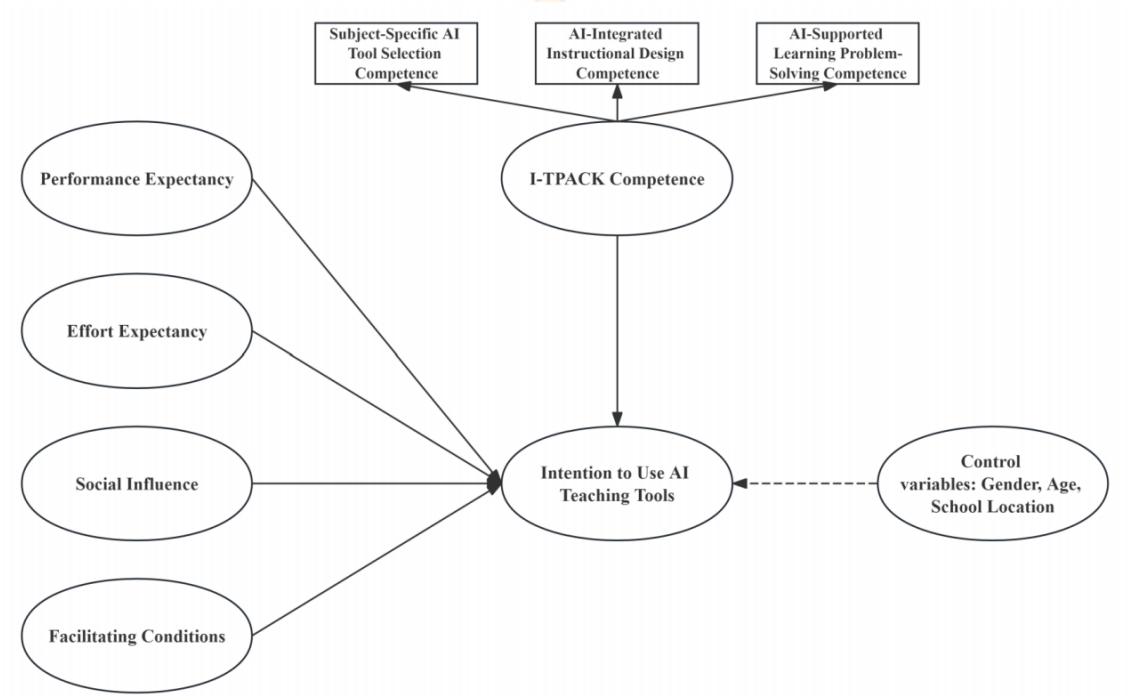


Figure 2. 2 Extended UTAUT theoretical framework of this study

2.6 Conclusion

Chapter 2 developed the theoretical basis for the empirical model. UTAUT was selected because it captures four central aspects of technology acceptance: expected performance benefits, the effort associated with use, relevant social expectations, and the support available for implementation. I-TPACK competence was added to represent a distinctly educational requirement—the ability to connect AI knowledge with pedagogy and subject content. The framework therefore explains adoption intention through both acceptance-related perceptions and professional competence. Behavioral intention is used as the principal outcome because actual classroom use may be limited by factors such as institutional rules, infrastructure, or access to suitable AI applications, whereas intention more directly represents teachers' current readiness to adopt. The next chapter translates this framework into the study's measurement, sampling, data-collection, and analytical procedures.

CHAPTER 3
METHODOLOGY

Chapter 3 describes how the empirical investigation was conducted. A quantitative design was used to examine the factors associated with primary school teachers' adoption of AI teaching tools in Southwest China. The chapter explains how the study variables were operationalized, how respondents were selected and the required sample size was determined, and how the online questionnaire was administered. It also sets out the analytical sequence, including descriptive statistics, internal-consistency assessment, confirmatory factor analysis (CFA), and structural equation modeling (SEM). Together, these procedures were used to evaluate the measurement model and test the relationships proposed in the theoretical framework.

3.1 Research Tools

3.1.1 Operational Definition of Variables

For clarity and consistency, the principal constructs examined in this research are operationally defined as follows:

Table 3. 1 Summary of Operational Definitions of Core Concepts

Concept	Operational Definition	Source
Performance Expectancy	Teachers perceive that the use of AI teaching tools can improve their teaching performance, work efficiency and students' learning outcomes.	Venkatesh et al. (2003)
Effort Expectancy	Teachers perceive the ease of using AI teaching tools, including the clarity of the interface, the learnability of the functions, and the simplicity of operation.	
Social Influence	The extent to which teachers perceive important others (school leaders, colleagues, students, parents) as requiring the use of AI teaching tools.	
Facilitating Conditions	Teachers perceive the organizational and technical infrastructure supporting their use of AI teaching tools, covering hardware resources, technical assistance, and compatibility assurance.	

Table 3. 1 (Continued)

Concept	Operational Definition	Source
I-TPACK Competence	Teachers' ability to effectively integrate technology, pedagogy and subject content knowledge specifically refers to the strategic knowledge of using artificial intelligence tools to solve specific subject teaching problems.	Mishra and Koehler (2006); Schmidt et al. (2009)
Intention to Use AI Teaching Tools	The subjective possibility of teachers to plan, intend or expect to use AI teaching tools in future teaching work.	Venkatesh et al. (2003)

3.1.2 Variable Measurement

The six constructs in the model were measured with a five-point Likert-type instrument. Respondents indicated their level of agreement from 1 (strongly disagree) to 5 (strongly agree). The final questionnaire contained 21 items covering performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and intention to use AI teaching tools.

(1) Performance Expectancy (PE)

Table 3. 2 Performance Expectancy Measurement Scale

Concept	Adapted items	Source
Performance Expectancy	PE1. AI-powered teaching tools can significantly enhance my instructional efficiency.	Venkatesh et al. (2003)
	PE2. AI teaching tools can help me speed up grading assignments and preparing lessons.	
	PE3. AI-powered teaching tools allow me to accomplish more teaching tasks within the same timeframe.	
	PE4. AI-powered teaching tools can help me achieve better teaching performance evaluations.	

(2) Effort Expectancy (EE)

Table 3. 3 Effort Expectancy Scale

Concept	Adapted items	Source
Effort Expectancy	EE1. The AI teaching tool features a clear and intuitive interface.	Venkatesh et al. (2003)
	EE2. For me, mastering AI teaching tools is a breeze.	
	EE3. Overall, I find AI teaching tools very easy to use.	
	EE4. Mastering the basic functions of AI teaching tools requires minimal effort.	

(3) Social Influence (SI)

Table 3. 4 Social influence Measurement Scale

Concept	Adapted items	Source
Social Influence	SI1. The school administration and teaching team leaders recommended that I adopt AI-powered teaching tools.	Venkatesh et al. (2003)
	SI2. Colleagues who have a significant impact on me are using AI teaching tools.	
	SI3. The school administration has provided clear support for promoting AI teaching tools.	

(4) Facilitating Conditions (FC)

Table 3. 5 Facilitating Conditions Scale

Concept	Adapted items	Source
Facilitating Conditions	FC1. The school provides sufficient hardware equipment, including computers, tablets, and smart blackboards, for me to use AI tools.	Venkatesh et al. (2003)
	FC2. I possess the necessary knowledge and skills to utilize AI-powered teaching tools.	
	FC3. The school's existing AI teaching tools are fully compatible with my commonly used teaching software, such as PPT and Seewo.	
	FC4. When I encounter technical issues while using AI tools, the school provides dedicated support staff to assist me.	

(5) I-TPACK competence

Table 3. 6 I-TPACK competence Measurement Scale

Construct	Adapted items	Source
I-TPACK competence	**TPACK1.** I can select appropriate AI tools to support teaching based on the characteristics of the subject I teach.	Schmidt et al. (2009)
	TPACK2. I can skillfully integrate AI tools into my instructional design, rather than using technology for its own sake.	
	TPACK3. I know how to use AI tools to address students' common learning difficulties in specific knowledge areas.	

(6) Intention to Use AI Teaching Tools

Table 3. 7 Measurement Scale of Intention to Use AI Teaching Tools

Concept	Adapted items	Source
Intention to Use AI Teaching Tools	**INT1.** For the upcoming semester, I plan to try or continue using AI teaching tools.	Venkatesh et al. (2003)
	INT2. I anticipate using AI tools more frequently in my future teaching.	
	INT3. I plan to use AI teaching tools at least once or twice a week to support my teaching.	

3.2 Data Collection Management

3.2.1 Target Population

The target population consisted of full-time primary school teachers employed in public or private schools in Sichuan, Yunnan, Guizhou, and Chongqing. The individual teacher was the unit of analysis.

The population of interest includes teachers from a range of subject specializations and school settings, covering urban districts, county-level locations, towns, rural communities, mountainous areas, and remote schools. Eligible respondents must be actively involved in classroom instruction or in teaching-related professional duties at a primary school.

Both public and private primary schools were included so that the sample could reflect different administrative and educational settings. These settings may vary in digital infrastructure, access to professional development, technical support, and availability of AI-related teaching resources. Covering all four provincial-level areas also allowed the study to represent the diversity of primary-school environments found across Southwest China.

Participation was limited to teachers who were employed full time in a public or private primary school in Sichuan, Yunnan, Guizhou, or Chongqing, performed regular teaching or teaching-related duties, and agreed voluntarily to join the survey. Individuals without regular classroom responsibilities, including administrative staff, substitutes, student teachers, retirees, and teachers working only in kindergartens, secondary schools,

vocational institutions, or universities, were not eligible.

On this basis, the study defines its target population as full-time teachers employed in public or private primary schools in Sichuan Province, Yunnan Province, Guizhou Province, and Chongqing Municipality.

3.2.2 Sampling Techniques

Purposive sampling was used to recruit full-time primary school teachers from public and private schools in Sichuan, Yunnan, Guizhou, and Chongqing. This approach ensured that respondents were actively involved in teaching and were therefore able to provide experience-based judgments about AI teaching tools and their potential use in school practice.

Questionnaires were distributed through contacts with schools, teacher communication groups, and regional education networks in the four study areas. Participants were recruited because their professional backgrounds corresponded to the research purpose. This approach also enabled the sample to include teachers from diverse institutional settings, including urban, county-level, rural, mountainous, and comparatively under-resourced schools in Southwest China.

Uniform inclusion and exclusion rules were used throughout recruitment. Eligible participants were full-time teachers employed by public or private primary schools in Sichuan, Yunnan, Guizhou, or Chongqing and were required to undertake regular classroom teaching or related professional duties. No restriction was imposed on age, subject specialization, teaching experience, or school location. The study excluded interns, administrative personnel without routine teaching responsibilities, teachers working outside primary education, and individuals located beyond the four selected regions.

Purposive sampling was appropriate because eligibility for the study depended on specific professional characteristics. The research required respondents who were members of the target population and who had current classroom experience relevant to questions about AI teaching tools. Applying predefined inclusion criteria also increased the likelihood that responses would be directly relevant to the study objectives. In practical terms, purposive recruitment was feasible for reaching teachers dispersed across provinces, cities, counties, towns, and rural areas in Southwest China.

3.2.3 Sample Size

An appropriate sample is necessary to obtain dependable measurements, stable parameter estimates, and sufficient statistical power. In multivariate analysis, one commonly applied rule of thumb links the number of participants to the number of observed measurement items. For studies requiring greater robustness and more stable estimates, approximately 20 respondents per item is recommended (Bujang et al., 2022).

The questionnaire contained 21 core measurement items across the six study constructs. Using a respondent-to-item ratio of 20:1, the minimum number of usable cases required for the main analysis was calculated as follows:

$$21 \times 20 \text{ r} = 420 \text{ valid responses}$$

The calculation produced a minimum requirement of 420 valid responses. This sample size was considered adequate for evaluating the measurement model and estimating the five direct relationships specified in the framework. A larger sample also supports greater statistical precision, stronger power for detecting meaningful associations, and more stable multivariate parameter estimates (Wang & Rhemtulla, 2021).

Because some returned questionnaires could be incomplete, contain patterned answers or missing information, or fail subsequent screening, the distribution target incorporated an estimated invalid-response allowance of approximately 20%. The number of questionnaires required for distribution was therefore determined using the following calculation:

$$420 \div (1 - 0.20) = 525 \text{ questionnaires}$$

Accordingly, the survey plan involves distributing at least 525 questionnaires to secure a minimum of 420 usable responses for subsequent statistical analysis. This target provides sufficient observations to assess measurement quality and to examine the hypothesized associations among the six latent constructs.

3.2.4 Data Collection Techniques

The questionnaire was administered online through Wenjuanxing. A link to the survey was circulated to eligible full-time primary school teachers through teacher WeChat and QQ groups in Sichuan, Yunnan, Guizhou, and Chongqing. These existing communication networks provided a practical means of distributing the invitation and allowing participants to access the electronic instrument directly.

Survey responses were gathered between March 10 and April 10, 2026. At the beginning of the survey, respondents received brief information about the research aims, participation criteria, voluntary involvement, and protection of response privacy. An informed-consent notice was provided before access to the survey items, and only those who agreed to participate continued with the questionnaire. The survey did not request any information that could directly identify individual respondents, and the collected data were retained exclusively for scholarly purposes.

The research was conducted in accordance with standard ethical requirements. Participation was entirely optional, and respondents retained the right to discontinue their involvement at any stage. No information capable of identifying individual participants was requested, and all collected responses were restricted to scholarly use. The survey introduction also provided participants with a brief description of the research aims, the intended respondent group, and the estimated time needed to complete the questionnaire.

Wenjuanxing was configured to require completion of all essential measurement items before a questionnaire could be submitted, and each participant was limited to one submission. Once data collection had closed, all returned questionnaires were reviewed using the study's predefined quality-screening rules.

A total of 525 questionnaires were distributed during the data-collection period. Screening of the returned surveys resulted in 502 usable cases, corresponding to a valid response rate of 95.62%. The final sample therefore exceeded the required minimum of 420. Before analysis, the retained cases were organized and checked, after which they were used for descriptive statistics, measurement-quality assessment, CFA, and hypothesis testing.

3.3 Data Analysis

3.3.1 Pilot study

A pilot study was conducted before the main survey with 30 primary school teachers in Southwest China. Its purpose was to identify problems with comprehension, administration, and the initial psychometric performance of the questionnaire. Pilot samples of roughly 20–30 participants are commonly used to detect difficulties in item wording, response formats, and survey procedures before full administration (Hertzog, 2008). The pilot questionnaire was delivered through Wenjuanxing.

After completing it, participants were invited to comment on item clarity, interpretation of the response scale, question ordering, and the usability of the online survey interface.

Pilot data were examined for item performance and internal consistency. Cronbach's alpha exceeded 0.70 for every construct, indicating acceptable consistency among the items. Corrected item-total correlations were also reviewed and showed that each item corresponded adequately with the remaining items in its scale. Given the small pilot sample of 30, the Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's test were interpreted only as preliminary evidence about factorability rather than as definitive validation of the measurement structure. Formal assessment of the model, including CFA, convergent validity, and discriminant validity, was therefore conducted again with the full study sample.

Feedback from pilot participants and the initial item diagnostics informed minor revisions to the instrument. Several statements were reworded to improve precision and reduce ambiguity, and the survey instructions and response procedures were refined to make completion more straightforward. These changes were intended to improve clarity and consistency without altering the underlying constructs. The resulting questionnaire was then used in the main study to measure performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and intention to use AI teaching tools.

The item-level pilot results are shown in Table 3.8. Across the 21 items, means ranged from 3.067 to 4.133, while standard deviations ranged from 0.890 to 1.368. Corrected item-total correlations varied from 0.673 to 0.862, all of which exceeded the conventional 0.30 criterion. These results indicated that responses showed adequate variation and that each item was sufficiently consistent with its intended scale. No item demonstrated problematic performance at the pilot stage; consequently, all 21 items were retained for the formal survey and later reliability and validity analyses.

Table 3. 8 Item analysis for pilot test

Item	Construct	Mean	SD	Corrected Item–Total Correlation
PE1	PE	3.433	1.04	0.728
PE2	PE	3.433	1.04	0.845
PE3	PE	3.2	1.243	0.776
PE4	PE	3.367	1.033	0.694
EE1	EE	4.133	0.9	0.803
EE2	EE	4.033	0.89	0.8
EE3	EE	3.967	1.098	0.862
EE4	EE	3.833	0.95	0.836
SI1	SI	3.433	1.278	0.793
SI2	SI	3.467	1.252	0.841
SI3	SI	3.7	1.368	0.805
FC1	FC	3.367	1.189	0.832
FC2	FC	3.433	1.278	0.843
FC3	FC	3.467	1.196	0.823
FC4	FC	3.3	1.149	0.8
ITPACK1	ITPACK	3.5	1.075	0.673
ITPACK2	ITPACK	3.333	1.093	0.712
ITPACK3	ITPACK	3.233	1.135	0.762
INT1	INT	3.333	1.184	0.823
INT2	INT	3.433	1.251	0.841
INT3	INT	3.067	1.202	0.787

Table 3.9 presents the internal-consistency coefficients obtained in the pilot study. Cronbach's alpha ranged from 0.878 to 0.922: 0.889 for performance expectancy, 0.922 for effort expectancy, 0.905 for social influence, 0.917 for facilitating conditions, 0.878 for I-TPACK competence, and 0.908 for intention to use AI teaching tools. Because every coefficient was above 0.70, each dimension demonstrated satisfactory internal consistency.

Table 3. 9 Pretest Reliability Statistics

Construct	Items	Cronbach's Alpha
PE	4	0.889
EE	4	0.922
SI	3	0.905
FC	3	0.917
ITPACK	4	0.878
INT	3	0.908

The overall pilot statistics are reported in Table 3.10. Cronbach’s alpha for the 21-item instrument was 0.900, exceeding the 0.70 criterion and indicating strong overall internal consistency. The Kaiser–Meyer–Olkin value was 0.719, which exceeded the 0.60 benchmark, and Bartlett’s test was significant, $\chi^2(210) = 552.801$, $p < 0.001$. Thus, the pilot data provided preliminary support for the reliability of the instrument and for proceeding with factor-based assessment. Because the pilot sample was limited, however, the factor structure and its convergent and discriminant validity were evaluated again using the larger main-study dataset.

Table 3. 10 Pre-investigation KMO and Bartlett's test

Overall Test	Value	Reference
Overall Cronbach's Alpha	0.9	> 0.70
KMO	0.719	> 0.60
Bartlett's χ^2	552.801	df = 210
Bartlett's p-value	< 0.001	< 0.05

3.3.2 Descriptive Statistical Analysis

Descriptive statistics provide a concise numerical account of the main characteristics of a dataset. They are used to organize and summarize observations so that patterns in the data can be interpreted more readily.

In this study, descriptive statistics were used to summarize both respondent characteristics and scores on the six constructs. Means and standard deviations described the general response levels and dispersion, while skewness and kurtosis were inspected to evaluate the shapes of the item distributions.

3.3.3 Reliability Analysis

Reliability analysis examines whether a measurement instrument produces sufficiently consistent scores across its items or repeated applications (Karnia, 2024). Tavakol and Dennick (2011) indicate that Cronbach's alpha (α) is used to assess the degree of internal consistency among items intended to measure the same construct. Cronbach's alpha takes values between 0 and 1, and larger coefficients generally reflect greater consistency among the items within a scale.

Reliability analysis was used to determine whether the questionnaire items measured their intended constructs with adequate internal consistency. Cronbach's alpha was calculated for each construct, using 0.70 as the minimum acceptable criterion. Corrected item-total correlations were also examined to identify items that did not correspond well with the remaining indicators in the same scale. Establishing satisfactory reliability was treated as a prerequisite to subsequent CFA and SEM. The resulting coefficients and item-level diagnostics are reported with the corresponding results.

3.3.4 Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) tests whether observed indicators conform to a measurement structure specified in advance from theory. The adequacy of a proposed measurement model can be evaluated by comparing its implied relationships with the observed data. Common indices used for this purpose include the chi-square statistic, root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker–Lewis index (TLI) (Shi et al., 2019).

CFA was used to evaluate the six-factor measurement model comprising performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and intention to use AI teaching tools. Each latent construct was linked to its designated observed items, allowing the analysis to assess whether the indicators represented their intended factors adequately.

The proposed factor structure was specified with reference to the theoretical framework and evidence reported in previous empirical studies. AMOS 24.0 was then used to examine how the observed indicators corresponded to their underlying latent factors. Model adequacy was evaluated through several fit indices rather than relying on a single statistic. The assessment considered the chi-square test together with RMSEA, CFI, and TLI, with RMSEA values below 0.08 and CFI and TLI values above 0.90 used as indicators of an acceptable model fit.

Standardized factor loadings were examined as part of the measurement assessment, with values above 0.50 treated as acceptable evidence that an item represented its latent construct. Model modification, when considered, was guided by both modification indices and theoretical justification. The CFA results were then used to judge whether the measurement model showed adequate reliability and validity before proceeding to the structural analysis.

3.3.5 Structural Equation Modeling

Structural equation modeling (SEM) allows multiple hypothesized relationships among latent variables to be estimated within a single analytical framework (Wulandari, 2022). In this study, SEM was used to evaluate whether the structural model was consistent with the observed data and to estimate the proposed direct effects. Model fit was assessed with the chi-square statistic together with RMSEA, CFI, and TLI.

The structural model tested five direct paths from performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence to intention to use AI teaching tools. The model was estimated in AMOS 24.0, and the direction, size, and statistical significance of each path coefficient were examined. Overall fit was evaluated using the same family of indices applied to the measurement model; RMSEA below 0.08 and CFI and TLI above 0.90 were treated as indicators of acceptable fit, alongside consideration of the chi-square statistic.

To reduce potential common method bias, the survey used anonymous participation, neutral wording, and separation of items by construct. Because all variables were nevertheless measured through the same self-report instrument, Harman’s single-factor test was also conducted as a supplementary diagnostic before interpretation of the SEM results.

These procedures were selected to match the proposed framework and to provide a systematic basis for testing the five hypothesized antecedents of primary school teachers' intention to use AI teaching tools.

3.3.6 Group Difference Analysis

Group differences in teachers' adoption intention were assessed using an independent-samples t test for gender and one-way analysis of variance (ANOVA) for age and school location. Equality of variances was checked with Levene's test. Where the omnibus ANOVA indicated statistically meaningful differences, post hoc comparisons were performed using Tukey's procedure under equal-variance conditions and the Games–Howell procedure when this assumption was not satisfied (Field, 2018). Statistical significance was evaluated at the 0.05 level. Descriptive and inferential results included group means, standard deviations, relevant test statistics, p values, and measures of effect magnitude. Cohen's d quantified the gender difference, whereas eta squared (η^2) was used to indicate the magnitude of variation associated with age and school location (Lakens, 2013).

3.4 Conclusion

Chapter 3 detailed the design and analytical procedures used in the study. A quantitative cross-sectional survey measured six constructs with a five-point Likert questionnaire. Full-time primary school teachers from public and private schools in Sichuan, Yunnan, Guizhou, and Chongqing formed the target population, and purposive sampling was used for recruitment. The minimum required sample was 420, while 502 valid questionnaires were ultimately retained. The chapter also described the pilot test, data screening, participant protections, common-method diagnostic, CFA, SEM, and group-difference analyses. The results generated from these procedures are presented in Chapter 4.

CHAPTER 4
RESULTS

Chapter 4 presents the empirical findings based on 502 valid questionnaires from primary school teachers in Southwest China. The analysis first describes the sample and the distribution of item responses. It then evaluates the measurement model through CFA, including overall model fit and evidence of convergent and discriminant validity. The structural model is subsequently estimated to test the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and intention to use AI teaching tools. The relative strength of the significant predictors is also compared.

4.1 Descriptive Analysis

4.1.1 Sample characteristics

Among the 502 respondents, women represented 64.14% of the sample and men 35.86%. The two largest age categories were 26–35 years (33.27%) and 36–44 years (30.08%), followed by teachers aged 45–54 years (21.51%). For teaching experience, 30.48% had worked for 8–15 years, 21.12% for 16–25 years, and 20.72% for 4–7 years. Bachelor's degree holders constituted 76.29% of respondents. With respect to professional title, Level I teachers accounted for 34.06% and Level II teachers for 32.47%, making these the two largest categories.

Regarding teaching subjects, Chinese accounted for 27.09% of respondents and mathematics for 24.70%, followed by Music, Physical Education, and Art at 16.14% and English at 13.55%. The largest share of teachers worked in county-level cities or counties (31.67%); 25.90% were in township or rural schools, 23.31% in prefecture-level city districts, and 19.12% in provincial-capital or municipal urban areas. Public-school teachers made up 88.84% of the sample, while 11.16% were employed in private primary schools. The final sample therefore included teachers from a range of demographic, professional, disciplinary, and geographical backgrounds relevant to the study context.

Table 4. 1 Sample Information

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
	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

Table 4. 1 (Continued)

Variable	Category	Frequency	Percentage
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

4.1.2 Descriptive statistics

Table 4.2 summarizes the response patterns for the 21 observed items representing the six dimensions. Item means fell between 3.452 and 3.763, showing that participants tended to report moderately favorable responses overall. PE3 produced the largest mean value (M = 3.763, SD = 0.730), reflecting relatively stronger perceptions that AI teaching tools can enhance work productivity. By comparison, SI1 showed the smallest mean (M = 3.452, SD = 0.785), suggesting a lower level of endorsement concerning the role of relevant others in shaping teachers' AI use. Standard deviations varied from 0.705 to 0.809, indicating sufficient spread in responses to reflect meaningful differences across participants' views and adoption-related intentions.

Item skewness values extended from −0.255 to 0.096, and kurtosis ranged from −0.483 to 0.065. These statistics did not indicate a substantial departure from univariate normality. The mildly negative skew observed for several items is consistent with the tendency of respondents to select the upper response categories. Overall, the distributions were sufficiently well behaved for the maximum-likelihood procedures used in the CFA and SEM analyses.

Table 4. 2 Descriptive Statistics Results

Item	Construct	Mean	SD	Skewness	Kurtosis
PE1	PE	3.739	0.733	-0.1	-0.307
PE2	PE	3.723	0.782	-0.175	-0.369
PE3	PE	3.763	0.73	-0.065	-0.371
PE4	PE	3.731	0.719	-0.068	-0.301
EE1	EE	3.707	0.748	-0.185	-0.079
EE2	EE	3.689	0.717	-0.081	-0.253
EE3	EE	3.651	0.761	-0.084	-0.206
EE4	EE	3.705	0.729	0.085	-0.483
SI1	SI	3.452	0.785	-0.04	-0.174
SI2	SI	3.51	0.741	-0.108	-0.137
SI3	SI	3.506	0.742	-0.065	-0.301
FC1	FC	3.506	0.731	-0.159	0.065
FC2	FC	3.472	0.73	0.02	-0.107
FC3	FC	3.52	0.705	0.032	-0.242
FC4	FC	3.478	0.733	0.015	-0.117
ITPACK1	ITPACK	3.614	0.775	-0.138	-0.212
ITPACK2	ITPACK	3.614	0.79	-0.049	-0.319
ITPACK3	ITPACK	3.61	0.72	0.096	-0.346
INT1	INT	3.687	0.734	-0.255	0.05
INT2	INT	3.715	0.809	-0.162	-0.472
INT3	INT	3.737	0.747	-0.137	-0.303

4.2 Confirmatory Factor Analysis

4.2.1 Measurement model and fit metrics

The measurement-model fit statistics are reported in Table 4.3. The chi-square value was 321.684 with 174 degrees of freedom, giving $x^2/df = 1.849$, below the reference level of 3.00. CFI = 0.967, TLI = 0.960, and IFI = 0.968, all above 0.90. The absolute residual indices were likewise satisfactory, with RMSEA = 0.041 and SRMR = 0.038, both below 0.08.

Considered together, these values indicated that the six-factor measurement specification fit the observed data adequately and could be used for subsequent reliability, validity, and structural analyses.

Table 4. 3 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	0.96	> 0.90
IFI	0.968	> 0.90
RMSEA	0.041	< 0.08
SRMR	0.038	< 0.08

4.2.2 Convergent validity

As shown in Table 4.4, all 21 standardized factor loadings were statistically significant at $p < 0.001$ and ranged from 0.707 to 0.812. The loading ranges were 0.755–0.787 for performance expectancy, 0.747–0.782 for effort expectancy, 0.766–0.794 for social influence, and 0.707–0.770 for facilitating conditions. I-TPACK indicators loaded between 0.796 and 0.812, whereas intention indicators ranged from 0.784 to 0.811. Every value was above 0.50 and most exceeded 0.70, providing acceptable evidence that the observed items represented their intended latent variables. On this basis, no item was removed from the measurement model.

Table 4. 4 Convergence 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

Table 4. 4 (Continued)

Construct	Item	Standardized Loading	p-value
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
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

4.2.3 Discriminant validity

Discriminant validity was examined with the Fornell–Larcker criterion in Table 4.5. The square roots of AVE were 0.767 for performance expectancy, 0.764 for effort expectancy, 0.783 for social influence, 0.749 for facilitating conditions, 0.806 for I-TPACK competence, and 0.799 for intention to use AI teaching tools. Each diagonal value exceeded the correlations involving the corresponding construct. Inter-construct correlations ranged from 0.170 to 0.509. The strongest association was between I-TPACK competence and intention ($r = 0.509$, $p < 0.001$), followed by the association between performance expectancy and intention ($r = 0.440$, $p < 0.001$). Both remained below the relevant square-root AVE values.

These comparisons indicate that the six constructs were empirically distinguishable under the Fornell–Larcker criterion. Although several constructs were positively related, their shared variance was not sufficiently high to suggest that they represented the same latent concept. Performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and intention were therefore retained as separate factors for the structural analysis.

Table 4. 5 Discriminant validity test

Construct	PE	EE	SI	FC	ITPACK	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		
ITPACK	0.362***	0.341***	0.241***	0.303***	0.806	
INT	0.44***	0.365***	0.17***	0.345***	0.509***	0.799

Note. ***$p < 0.001$.

4.3 Structural model path analysis

Harman's single-factor test was used as a diagnostic for common method bias. An unrotated exploratory factor analysis including all measurement items showed that the first factor explained 36.27% of total variance. Because this proportion was below 50%, the results did not suggest that a single common factor dominated the covariance among the measures.

The structural estimates and hypothesis decisions are presented in Table 4.6. Performance expectancy showed a significant positive association with intention to use AI teaching tools ($\beta = 0.242$, $t = 6.149$, $p < 0.001$), supporting H1. Effort expectancy was also positively related to intention ($\beta = 0.148$, $t = 3.779$, $p < 0.001$), so H2 was supported. Social influence, however, was not significant ($\beta = -0.027$, $t = -0.715$, $p = 0.475$), and H3 was not supported. Facilitating conditions had a significant positive relationship with intention ($\beta = 0.144$, $t = 3.676$, $p < 0.001$), supporting H4.

I-TPACK competence produced the largest positive standardized coefficient ($\beta = 0.333$, $t = 8.244$, $p < 0.001$), providing support for H5.

Ranking the standardized coefficients shows that I-TPACK competence had the strongest association with teachers' intention to use AI teaching tools. Performance expectancy was the second-largest predictor, while effort expectancy and facilitating conditions had smaller and very similar coefficients, with effort expectancy marginally higher. Social influence did not contribute a statistically significant direct effect. Thus, four hypotheses were supported, and the pattern of coefficients gives greater weight to professional competence, expected instructional benefits, ease of use, and enabling conditions than to perceived social pressure.

Table 4. 6 Path effects

Hypothesis	Path	Standardized β	SE	t/CR	p	Decision
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	ITPACK → INT	0.333	0.04	8.244	< 0.001	Supported

4.4 Group Difference Analysis

Table 4.7 reports the group-comparison results for gender, age, and school location. The gender comparison was not significant, $t(500) = -0.598$, $p = 0.550$, $d = 0.056$, indicating very similar intention levels for male and female teachers. Age groups differed significantly, $F(4, 497) = 3.014$, $p = 0.018$, $\eta^2 = 0.024$, and the younger groups—particularly those below 35—reported higher average intention than older teachers. School location also produced a significant difference, $F(3, 498) = 2.953$, $p = 0.032$, $\eta^2 = 0.017$. Intention was highest among teachers in provincial-capital or municipal urban schools and lowest among those in township or rural schools. The η^2 values were small, however, indicating that age and location explained only a limited proportion of variation in intention.

Table 4. 7 Group Differences in Intention to Use AI Teaching Tools

Variable	Category	n	Mean	SD	Test Statistic	p	Effect Size
Gender	Male	180	3.69	0.66	t(500) = -0.598	0.55	d = 0.056
	Female	322	3.726	0.64			
Age	Under 25	44	3.8	0.61	F(4, 497) = 3.014	0.018	η2 = 0.024
	26–35	167	3.8	0.62			
	36–44	151	3.73	0.65			
	45–54	108	3.61	0.67			
	55 and above	32	3.45	0.69			
School location	Provincial capital/municipality urban area	96	3.82	0.6	F(3, 498) = 2.953	0.032	η2 = 0.017
	Prefecture-level city district	117	3.76	0.62			
	County-level city/county	159	3.71	0.65			
	Township/rural area	130	3.58	0.68			

4.5 Conclusion

Chapter 4 documented the descriptive results, measurement-model assessment, structural estimates, and group comparisons. Four predictors—performance expectancy, effort expectancy, facilitating conditions, and I-TPACK competence—showed significant positive relationships with intention, whereas social influence was non-significant. I-TPACK competence had the largest standardized effect. The supplementary comparisons found no meaningful gender difference, but small significant differences by age and school location. Teachers aged 26–35 reported higher intention than those aged 55 and above, and teachers in provincial-capital or municipal urban schools reported higher intention than teachers in township or rural schools. These findings provide the empirical basis for the discussion and implications developed in Chapter 5.

CHAPTER 5
DISCUSSION AND CONCLUSION

Chapter 5 interprets the empirical findings in light of the research objectives, theoretical framework, and prior studies. It considers how performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence are related to primary school teachers' intention to use AI teaching tools in Southwest China and identifies the factor with the largest effect. Differences in intention by gender, age, and school location are also discussed. The chapter then develops the theoretical contributions and practical implications of the results, acknowledges the study's limitations, and proposes directions for further research.

RQ1: How do performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence affect primary school teachers' intention to use AI teaching tools in Southwest China?

Four of the five proposed antecedents showed statistically significant relationships with adoption intention. Performance expectancy, effort expectancy, and facilitating conditions were each positively associated with teachers' willingness to use AI teaching tools, and I-TPACK competence produced the largest standardized effect. Social influence, in contrast, was not significant. The overall pattern indicates that teachers' intentions are more closely related to what they expect AI to contribute to teaching, how manageable the tools appear, whether practical support is available, and whether they possess the competence to integrate AI pedagogically than to pressure or encouragement from others.

The significant positive effect of performance expectancy suggests that teachers are more willing to use AI teaching tools when they anticipate tangible improvements in instructional work and professional effectiveness. This interpretation is consistent with the descriptive statistics: the PE items had comparatively high means, and PE3 recorded the highest item mean in the study. Such a pattern is understandable in primary education, where teachers repeatedly prepare lessons and worksheets, organize classroom activities,

provide feedback, and develop materials for pupils with different learning needs. AI becomes valuable when it can reduce repetitive work, assist in drafting lesson structures, suggest classroom-interaction prompts, support individualized resource creation, and shorten the time needed to prepare feedback. Recent evidence similarly shows that educators use generative AI to create instructional resources, plan lessons, design assessment activities, and support explanations of subject matter (Moundridou et al., 2024). Performance expectancy is therefore relevant because adoption intention depends partly on whether teachers can see practical benefits in their routine work. For schools and developers, this means that the value of AI should be demonstrated through concrete teaching tasks—such as reducing preparation time, accelerating feedback, and supporting differentiated instruction—rather than promoted only as a technologically advanced innovation.

Effort expectancy had a significant positive relationship with adoption intention, showing that usability remains important even when teachers recognize the potential instructional value of AI. Primary school teachers already balance teaching, classroom management, communication, and administrative tasks; consequently, tools that require complex interfaces, difficult prompting, extensive revision, or prolonged trial and error can create an additional burden. Ease of use therefore has both a technical and a workload-related meaning. Mohamed et al. (2025) similarly found that operational simplicity is associated with greater willingness to engage with generative AI while users are still developing familiarity with such systems. In practical terms, teachers are more likely to intend to use tools that offer clear interfaces, Chinese-language support, editable results, subject-oriented templates, and uncomplicated workflows.

Facilitating conditions were also a significant positive predictor, which underscores the practical importance of the environment in which teachers are expected to use AI. Reliable internet access, appropriate devices, compatible software, technical assistance, and institutional arrangements can make adoption substantially easier. This result is consistent with the UTAUT view that technology use depends not only on expected benefits and effort but also on whether users have the resources needed for implementation (Venkatesh et al., 2003). The issue is especially salient in Southwest China because the study covers urban, county, rural, mountainous, and remote schools. In settings where networks are unstable, equipment is outdated, approved platforms are

unavailable, technical staff are absent, training is limited, or rules for data and content are unclear, teachers may find AI difficult to incorporate regardless of their interest. Facilitating conditions should therefore be understood as concrete provision—connectivity, devices, platform access, troubleshooting, professional learning, time for experimentation, and clear rules on privacy, content verification, and responsible use—rather than as general expressions of institutional support.

I-TPACK competence had the largest relationship with intention, indicating that teachers' willingness to use AI is strongly connected with their ability to translate technological functions into pedagogically and subject-appropriate practice. Teachers with stronger competence can select tools for specific learning purposes, evaluate generated information critically, align AI use with curriculum objectives, and modify activities for pupils' developmental needs. This finding adds an important professional dimension to UTAUT: adoption is not explained only by usefulness and ease-of-use perceptions but also by the teacher's capacity to make informed instructional judgments. The result is consistent with arguments that AI-related pedagogical competence is central to teachers' acceptance and integration of intelligent technologies (Celik, 2023).

I-TPACK competence may have emerged as the strongest predictor because primary teaching requires more than convenient access to quickly generated content. Teachers must decide whether AI outputs are correct, compatible with curriculum standards, suitable for children's developmental level, and capable of being converted into worthwhile classroom learning. A teacher may be able to prompt an AI system to produce a lesson plan yet still be unable to detect conceptual errors, simplify explanations for younger pupils, select examples that fit students' experiences, redesign activities for classroom interaction, or avoid overreliance on automated feedback. Professional competence therefore provides explanatory value beyond general perceptions of usefulness and ease. This result is consistent with the Intelligent-TPACK perspective, which conceptualizes effective educational AI use as requiring technical understanding, pedagogical judgment, subject expertise, ethical sensitivity, and critical evaluation of generated content (Zou et al., 2025). In this sense, I-TPACK competence provides the professional mechanism through which access to AI can be translated into instructionally appropriate practice.

Social influence did not show a significant direct relationship with adoption intention once the other predictors were considered. This means that perceived expectations from school leaders, colleagues, parents, and other relevant groups added little explanatory value beyond teachers' own competence, expected instructional benefits, perceived ease, and available support. The relatively low score for SI1 (M = 3.452, SD = 0.785) is consistent with this pattern. The non-significant coefficient should therefore be interpreted as substantive evidence rather than as a model failure. One explanation is that encouragement or pressure alone is insufficient when teachers still need to judge whether AI is useful, manageable, ethically acceptable, and supported in practice. Another possibility is that AI use in primary education remains an evolving area in which policies, norms, and implementation rules are not yet sufficiently stable to create strong normative pressure. Shi et al. (2025) similarly suggest that social expectations can become less influential when technology decisions are driven mainly by professional judgment, perceived value, and ease of use.

RQ1 is therefore answered by a pattern in which performance expectancy, effort expectancy, facilitating conditions, and I-TPACK competence were significant positive predictors of intention, while social influence was not. Teachers' willingness to adopt AI appears to depend more on whether the technology delivers useful instructional outcomes, can be operated without excessive difficulty, is supported by workable school conditions, and can be integrated competently into teaching than on policy signals or peer expectations.

RQ2: Which of these factors has the strongest effect on primary school teachers' intention to use AI teaching tools in Southwest China?

The standardized coefficients provide a clear answer to RQ2: I-TPACK competence had the largest effect on intention. Its coefficient was greater than those for performance expectancy, effort expectancy, facilitating conditions, and social influence, making AI-related pedagogical competence the most influential factor in the model.

The finding also indicates that simple familiarity with digital technology does not adequately explain teachers' readiness to adopt AI. What matters more is whether teachers can convert AI capabilities into pedagogically relevant action. This supports extending UTAUT with a professional-competence construct tailored to teachers and suggests that the development of I-TPACK should occupy a central place in school-based training and continuing professional development.

Performance expectancy was the second-strongest predictor, confirming that teachers place considerable weight on the practical value of AI for their work. Its effect was nevertheless smaller than that of I-TPACK competence, implying that recognizing usefulness is not enough to produce the highest level of readiness. Teachers are more likely to act on perceived benefits when they also know how to evaluate and apply AI appropriately. Effort expectancy and facilitating conditions were significant but smaller predictors, indicating supporting roles for usability and school provision. This ranking has direct practical implications: professional development should emphasize AI-supported lesson design, output checking, curriculum alignment, and ethical use; developers should make instructional benefits visible while reducing unnecessary complexity; and schools should provide time, resources, technical help, and clear rules. The non-significant social-influence result further suggests that encouragement is more likely to matter when it is translated into practical support and competence development.

RQ3: Does primary school teachers' intention to use AI teaching tools in Southwest China differ according to gender, age, and school location?

No significant gender difference was identified in intention to use AI teaching tools. Male and female respondents reported almost the same level of readiness, and the very small effect size indicates that gender explained little variation in the outcome. Thus, the current sample does not support the view that male and female primary school teachers differ systematically in their willingness to adopt AI. This is compatible with recent educational technology research reporting smaller gender gaps when teachers have comparable access to training and institutional resources (Zhang et al., 2023; Li & Wang, 2024).

Intention differed significantly across the five age groups, with teachers aged 26–35 reporting higher intention than those aged 55 and above. Mean scores also tended to decline across the older groups. This pattern may reflect differences in familiarity with emerging AI applications, perceived learning demands, or access to AI-related professional development. The effect size was small, however, so age explained only a limited amount of variation. Because chronological age is related to teaching experience, previous technology exposure, and training opportunities, the result should not be interpreted causally. Chen et al. (2025) likewise suggest that apparent age differences in educational AI adoption may be better understood through digital competence and prior

technology experience. Targeted professional learning may therefore help reduce the observed gap.

School location likewise showed a statistically significant association with intention, although the magnitude of the difference was small. Teachers in provincial capitals or municipality urban areas expressed stronger intention than teachers in township or rural schools. Possible contextual explanations include differences in connectivity, availability of devices and AI platforms, technical support, and opportunities for professional learning. This pattern is consistent with recent evidence that urban-rural gaps in educational-technology adoption remain observable even as improvements in infrastructure and policy support gradually extend to rural and remote areas (Huang et al., 2024).

In summary, the evidence for RQ3 indicates no statistically significant difference in intention by gender, while both age and school location were associated with statistically significant but small differences. These supplementary findings add a demographic and contextual perspective to the relationships identified in the structural model.

5.1 Implication to Theories

The main theoretical contribution is a more education-specific explanation of AI adoption among primary school teachers. Rather than treating adoption as a generic response to a new technology, the study extends UTAUT with I-TPACK competence and evaluates the model in the institutional and regional conditions of Southwest China. Four theoretical implications follow from the results.

First, the findings support the applicability of UTAUT to in-service primary school teachers in Southwest China. UTAUT explains technology-related intention through performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). In the present data, performance expectancy, effort expectancy, and facilitating conditions were significant positive predictors of intention, demonstrating that practical value, usability, and implementation support remain important in teachers' decisions. This pattern is consistent with recent work showing that educators' engagement with AI is associated with perceived usefulness, ease of operation, and institutional provision (Linus et al., 2025). The present contribution lies in extending this evidence to practicing primary school teachers across urban, county, rural,

mountainous, and remote settings in Southwest China. UTAUT therefore retains explanatory value in this context, although the diversity of local resources and professional-learning opportunities remains important for interpretation.

Second, adding I-TPACK competence extends UTAUT beyond general technology perceptions by incorporating a form of professional capability specific to teaching. The conventional UTAUT constructs capture whether a technology appears useful, manageable, socially supported, and feasible, but they do not directly assess whether a teacher can integrate AI with curriculum, pedagogy, and pupils' developmental needs. I-TPACK competence was not only significant but also the strongest predictor in the model. This indicates that teachers' intentions are closely related to their ability to evaluate AI-generated information, align applications with curriculum objectives, adapt AI-supported activities for young learners, and manage ethical issues. The result supports the argument that meaningful educational AI use requires technological, pedagogical, content, and ethical competence in combination (Celik, 2023). Although AI literacy and teacher AI competence have received increasing attention (Ng et al., 2021), they are still not routinely integrated into technology-acceptance models. The present model therefore links acceptance theory with teacher professional knowledge and provides a more education-specific account of behavioral intention.

Third, the non-significant effect of social influence qualifies the conventional UTAUT expectation that important others shape behavioral intention (Venkatesh et al., 2003). In this sample, perceived expectations from leaders, colleagues, parents, or other relevant groups did not make an independent contribution once the remaining predictors were taken into account. This differs from studies that report stronger normative effects on educators' AI adoption (Korchak et al., 2025), but it is compatible with the view that teachers increasingly rely on professional judgment when evaluating new educational technologies (Chiu, 2021). In a still-developing area such as primary-school AI use, teachers may prioritize instructional value, usability, competence, and concrete support over social pressure. The finding therefore suggests that the relative importance of UTAUT constructs can vary by professional and technological context.

Fourth, the group comparisons identify contextual boundaries around adoption intention. Gender was not associated with a significant difference, whereas age and school location showed statistically significant but small differences. These results imply

that demographic and school-setting characteristics may shape the conditions under which AI is adopted, but their influence should not be overstated. This pattern is broadly consistent with evidence from Chinese K–12 teachers showing that demographic heterogeneity in generative AI adoption tends to be limited and dependent on the specific pathway examined (Zhang et al., 2026).

In summary, the study contributes to theory in four ways. It applies UTAUT to an underexamined population of in-service primary school teachers in Southwest China; demonstrates that I-TPACK competence adds a teacher-specific professional dimension with substantial explanatory value; shows that social influence is not necessarily a significant direct driver of AI adoption intention; and identifies small contextual differences by age and school location. By combining acceptance perceptions with professional capability, the model responds to calls for educational AI research to move beyond generic technology attitudes and to consider what teachers actually need to integrate AI into instruction (Celik, 2023).

5.2 Implication to Practitioners

The strongest practical implication concerns teacher professional development because I-TPACK competence had the largest effect on intention. Training should therefore move beyond introductory explanations of AI or demonstrations of individual functions. Programs need to develop teachers' ability to judge, modify, and integrate AI-generated content within curriculum-based teaching. General-purpose tools such as Doubao, Yuanbao, Kimi, and DeepSeek can assist with lesson planning, material generation, summarization, exercise preparation, and preliminary feedback, but access alone does not ensure appropriate classroom use. Training can be organized around authentic tasks—for example, revising an AI-generated lesson plan, verifying factual explanations, adapting language to pupils' cognitive level, designing subject-specific questions, and converting generic outputs into teachable activities. Subject-focused workshops, prompt practice, classroom simulations, AI-output evaluation, ethical cases, and peer review can help teachers progress from operating AI to exercising professional judgment about when and how it should be used.

Second, the results provide direction for the design and refinement of AI teaching tools. Both performance expectancy and effort expectancy were positively related to adoption intention, implying that teachers are more receptive to systems that deliver recognizable instructional benefits without imposing unnecessary operational complexity. To strengthen performance expectancy, tools should support recurring activities such as lesson preparation, worksheet production, differentiated-resource design, formative assessment, classroom-activity planning, and feedback drafting. Developers should demonstrate these task-level benefits rather than relying primarily on claims about technological sophistication. To strengthen effort expectancy, systems should offer straightforward interfaces, Chinese-language guidance, editable outputs, curriculum-oriented templates, subject-specific prompts, and clear procedures for revising generated materials. Because primary school teachers already carry substantial instructional and classroom-management workloads, complicated setup requirements, extensive prompt training, or repeated manual correction may discourage continued use. Appropriate safeguards should also be incorporated, including reminders to verify sources, prompts for factual checking, age-sensitive language settings, privacy protection, and warnings about unsuitable content.

School management represents another practical area. Because facilitating conditions significantly predicted intention, support needs to be visible in everyday working arrangements rather than limited to general encouragement. Schools should ensure dependable connectivity, appropriate devices, approved AI platforms, technical troubleshooting, shared resources, and sufficient time for teachers to experiment. School-based training and teaching-research activities can provide opportunities to compare AI outputs, discuss classroom applications, and develop subject-specific examples. Clear rules should also address privacy, student data, factual verification, copyright, and the boundary between AI assistance and teacher responsibility. Given the non-significant social-influence effect, compulsory targets or promotional slogans alone are unlikely to be effective. Leadership is more useful when it creates workable conditions through technical help, manageable training schedules, peer mentoring, and open exchange about both successful and unsuccessful uses.

The group results suggest differentiating support according to demonstrated needs rather than demographic stereotypes. Because gender differences were non-significant, the data do not justify separate training strategies for male and female teachers. Provision should instead respond to actual competence and experience. Older teachers who need additional assistance may benefit from slower-paced workshops, repeated hands-on practice, peer mentoring, and more time to become familiar with AI tools. Township and rural schools may require priority investment in stable connectivity, suitable hardware, dependable platforms, technical support, and accessible training. Since the observed age and location effects were small, these characteristics should be used as indicators of possible support needs rather than as assumptions about an individual teacher's willingness or ability.

Regional policy should likewise reflect the uneven implementation conditions across Sichuan, Chongqing, Yunnan, and Guizhou. A single model of AI adoption is unlikely to fit schools with markedly different infrastructure, training access, technical support, and institutional readiness. Better-resourced urban schools may benefit from advanced development in AI-supported lesson design, assessment, and ethical governance, whereas county, rural, mountainous, and remote schools may first need reliable networks, updated devices, trustworthy platform access, and regular technical services. Regional authorities can support shared resource platforms, online professional-development modules, demonstration lessons, school-university partnerships, and teacher communities that connect schools with different resource levels. Such measures directly address the importance of facilitating conditions and I-TPACK competence identified in the study and focus policy attention on reducing gaps in access, training, and implementation capacity.

5.3 Limitations of the Study and Implications for Future Research

The cross-sectional design provides information about teachers' perceptions at one point in time. It is suitable for estimating statistical associations among performance expectancy, effort expectancy, social influence, facilitating conditions, I-TPACK competence, and adoption intention, but it does not establish causal direction. Significant path coefficients should therefore be interpreted as relationships rather than proof that one variable cause another. The same caution applies to the age and school-location

comparisons, which identify group differences without demonstrating that age or location itself produces those differences. For example, the strong association between I-TPACK competence and intention does not mean that an increase in competence will automatically lead to higher intention in every context. Perceptions may change as teachers gain experience with Doubao, Yuanbao, Kimi, and DeepSeek, receive additional training, or work under new school policies. Longitudinal studies could examine how AI-related competence, perceived usefulness, perceived ease of use, and intention develop over time and would provide stronger evidence about temporal ordering and stability.

A second limitation is the reliance on self-reported questionnaire data. Teachers' ratings of their AI-related pedagogical competence, facilitating conditions, and adoption intention may be influenced by social desirability, recall limitations, or differences in how questions are interpreted. Measuring all constructs through one survey also leaves the possibility of residual common method variance. Although the survey enabled efficient data collection from a large sample, it does not directly show how AI is used in everyday lessons. Future research could triangulate questionnaires with interviews, classroom observations, teaching portfolios, AI-supported lesson plans, or platform-use records. Such evidence would make it possible to examine how teachers evaluate AI outputs, modify them for primary pupils, and respond to practical difficulties during actual instruction.

The geographical and educational scope also limits generalization. The sample comprised full-time primary school teachers from Sichuan, Yunnan, Guizhou, and Chongqing; although these areas contain varied urban, county, rural, mountainous, and remote settings, results may differ elsewhere in China or at other educational levels. Infrastructure, governance, professional development, curriculum requirements, and local digitalization policies are not uniform across regions. The group analyses in this study compared mean intention by gender, age, and school location but did not estimate their adjusted effects after controlling for performance expectancy, effort expectancy, social influence, facilitating conditions, and I-TPACK competence, nor did they test whether structural paths differed across groups. Unequal subgroup sizes, especially the smaller number of teachers aged 55 and above, may also have reduced the stability of some comparisons. Because age and location effect sizes were small, these findings

require cautious interpretation. Future work could compare eastern, central, western, and northeastern China and different levels of education. After measurement invariance has been established, multi-group SEM could test whether structural relationships vary by gender, age, school location, subject, teaching experience, prior AI training, or frequency of AI use. Hierarchical regression or SEM could additionally estimate adjusted demographic and contextual effects alongside the principal theoretical predictors.

A further limitation is that the outcome was intention rather than observed AI use. Behavioral intention is closely related to adoption decisions, but willingness does not ensure sustained classroom implementation. Teachers may intend to use AI yet be prevented by school regulations, lack of approved platforms, weak connectivity, workload pressure, privacy concerns, or insufficient technical help. The results should therefore not be interpreted as evidence of actual classroom behavior. Future models could include actual use, continued-use intention, or frequency of AI use and could combine self-reports with platform records, observations, or samples of AI-assisted teaching materials to determine whether stated readiness is translated into practice.

Future studies can strengthen the evidence base by combining longitudinal designs with qualitative interviews, classroom observations, and objective indicators of AI use. Larger and more balanced subgroups would permit stronger group comparisons, while measurement-invariance testing, adjusted control-variable models, and multi-group analyses could clarify the role of demographic and contextual characteristics. Adding actual use behavior would also connect the formation of intention with the later implementation of AI in classroom practice.

5.4 Conclusion

This study examined the intention of primary school teachers in Southwest China to use AI teaching tools through an extended UTAUT model that incorporated I-TPACK competence. I-TPACK competence had the largest positive relationship with adoption intention, while performance expectancy, effort expectancy, and facilitating conditions were also significant positive predictors. Social influence did not show a significant direct effect. The findings therefore suggest that teachers' readiness to use AI is linked principally to professional competence, expected instructional value, usability, and concrete implementation support rather than to normative pressure from others.

The supplementary group comparisons indicated no statistically significant difference in intention by gender. Statistically significant differences were observed for age and school location, but the corresponding effect sizes were small. Teachers aged 26–35 expressed stronger intention than those aged 55 years and above, and respondents working in provincial-capital or municipality urban schools reported stronger intention than those in township or rural schools. These patterns imply that some demographic and contextual variation exists, although its limited magnitude means that such differences are less influential than the professional-competence and technology-acceptance predictors tested in the structural model.

Overall, AI adoption among primary school teachers is best understood as a decision grounded in professional capability and practical feasibility. Building I-TPACK competence, demonstrating clear instructional benefits, making tools easier to operate, and ensuring reliable school support appear more consequential than symbolic promotion or assumptions based on demographic categories. Some older teachers and teachers in township or rural schools may nevertheless require additional opportunities and resources. The study thus provides a context-specific explanation of adoption intention that emphasizes both professional capacity building and equitable conditions for implementation.

BIBLIOGRAPHY

Băiceanu, C. M., Bădoi-Hammami, M., & Popa, C. S. Artificial Intelligence Literacy in Teacher Education: Towards a Pedagogical Framework for. *Journal of Contemporary Applied Researches, 8,* 1-15. https://doi.org/10.56177/epvl.ch21.2025.en

Bahroun, Z., Anane, C., Ahmed, V., & Zacca, A. (2023). Transforming education: A comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis. *Sustainability*, *15*(17), 12983.

Bujang, M. A., Sa'at, N., & Sidik, T. (2022). Determination of Minimum Sample Size Requirement for Multiple Linear Regression and Analysis of Covariance Based on Experimental and Non-experimental Studies. *Epidemiology, Biostatistics, and Public Health*, *14*, e12117-12111. https://doi.org/10.2427/12117

Calleja, J., & Camilleri, P. (2025). Primary school teachers' perceptions towards the use of generative AI in teaching using lesson study. *International Journal for Lesson and Learning Studies*, *14*(3), 237-252. https://doi.org/10.1108/IJLLS-11-2024-0268

Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. *Technological Forecasting and Social Change*, *201*, 123247. https://doi.org/10.1016/j.techfore.2024.123247

Celik, I. (2023). Exploring the determinants of artificial intelligence (AI) literacy: Digital divide, computational thinking, cognitive absorption. *Telematics and Informatics*, *83*, 102026.

Chang, Y., Ni, Y., & Zhang, X. (2025). Virtual Reality in Cultural Tourism: Optimizing Learning and Interactive Experiences. *International Journal of Web-Based Learning and Teaching Technologies*, *20*(1), 387387. https://doi.org/10.4018/IJWLTT.387387

Chen, Y., Zhang, L., & Liu, X. (2025). Generative AI adoption in K–12 education: Digital competence and training as key mediators. *Frontiers in Psychology, 16*, 1588047. https://doi.org/10.3389/fpsyg.2025.1588047

Chen, R., Wu, Y., Chen, Z., & Zhou, P. (2025). Advancing educational equity in rural China: the impact of AI devices on teaching quality and learning outcomes for sustainable development. *Frontiers in Psychology*, *16*, 1588047. https://doi.org/10.3389/fpsyg.2025.1588047

Chen, Y. (2026). Teachers' generative AI literacy on their perceptions of generative AI in education: self-efficacy as a mediator. *International Journal of Mobile Learning and Organisation*, *24*(2),101411. https://doi.org/10.1504/IJMLO.2025.10069198

Chiu, T. K. F. (2021). A Holistic Approach to Artificial Intelligence (AI) Curriculum for K-12 Schools. *TechTrends,65*(5),796-807. https://doi.org/10.1007/s11528-021-00637-1

Chiu, T. K. F. (2025). Developing intelligent-TPACK (I-TPACK) framework from unpacking AI literacy and competency: implementation strategies and future research direction. *Interactive Learning Environments*, *33*(7), 4189-4192. https://doi.org/10.1080/10494820.2025.2545053

Cooksey, R. W. (2020). Descriptive statistics for summarising data. In *Illustrating statistical procedures: Finding meaning in quantitative data*, 61-139.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). Technology acceptance model. *Journal of Management Sciences*, *35*(8), 982-1003.

Deb, D.-J., & Sofal, F. (2026). TPACK to I-TPACK: A Systematic Analysis of I-TPACK (Integrating Intelligence or Artificial Intelligence with Technological Pedagogical Content Knowledge). *International journal of Emerging Voices in Education*, *2*(1), 1-11. https://doi.org/10.59828/ijeve.v2i1.26

Elom, C. O., Onyeneke, R. U., Ayerakwa, H. M., Atta-Ankomah, R., Deffor, E. W., & Uwaleke, C. C. (2024). The role of information and communication technologies and access to electricity on education in Africa. *Education and Information Technologies*, *29*(12), 15501-15532.

Field, A. (2018). *Discovering statistics using IBM SPSS statistics (5th ed.)*. SAGE Publications.

Feng, J., Yu, B., Tan, W. H., Dai, Z., & Li, Z. (2025). Key factors influencing educational technology adoption in higher education: A systematic review. *PLOS Digit Health*, *4*(4), e0000764. https://doi.org/10.1371/journal.pdig.0000764

Fokides, E., & Peristeraki, E. (2025). Comparing ChatGPT's correction and feedback comments with that of educators in the context of primary students' short essays written in English and Greek. *Education and Information Technologies*, *30*(2), 2577-2621. https://doi.org/10.1007/s10639-024-12912-8

Gamlem, S. M., Johnston, S.-K., Moltudal, S., McGrane, J., & Hopfenbeck, T. N. (2026). Generative AI in initial teacher education: Exploring the alignment of perceptions and experiences of pre-service teachers and their teacher educators. *Teaching and Teacher Education*, *172*, 105382. https://doi.org/10.1016/j.tate.2026.105382

Guo, Y.-z., Zhou, Y., & Liu, Y. (2020). The inequality of educational resources and its countermeasures for rural revitalization in southwest China. *Journal of Mountain Science*, *17*, 304-315. https://doi.org/10.1007/s11629-019-5664-8

Hertzog, M. A. (2008). Considerations in determining sample size for pilot studies. *Research in Nursing & Health*, *31*(2), 180-191.

Huang, X., & Zhang, S. (2025). Teachers' generative AI-facilitated informal learning: A scope review. *European Journal of Teacher Education*, *48*, 1-26. https://doi.org/10.1080/02619768.2025.2571920

Huynh, L., Le, T. H., Dang, B., An, B. T., Vu, C. T., & Nguyen, A. (2025). Mindset matters: Fostering teachers' responsible AI use through professional development. *Journal of New Approaches in Educational Research*, *14*(1), 23. https://doi.org/10.1007/s44322-025-00043-y

Huang, R., Spector, J. M., & Yang, J. (2024). Educational technology equity in rural China: Infrastructure and policy implications. *Computers & Education, 198*, 104789. https://doi.org/10.1016/j.compedu.2024.104789

Jerrim, J., Prieto-Latorre, C., Marcenaro-Gutierrez, O. D., & Shure, N. (2025). Teacher self-efficacy, instructional practice, and student outcomes: Evidence from the TALIS video study. *American Educational Research Journal*, *62*(2), 378-413.

Jiangsu Network Information. (2025). *The country's first "Ethical Guidelines for Primary School Students' Use of AI" has been released!* https://jswx.gov.cn/chuanbo/tongxinyuan/202512/t20251211_1149312.shtml

Karnia, R. (2024). Importance of Reliability and Validity in Research. *Psychology and Behavioral Sciences*, *13*, 137-141. https://doi.org/10.11648/j.pbs.20241306.11

Kayıran, D., Sönmez, M., Avcı, A., & Haji Mohamud, R. Y. (2026). Teachers' perceptions of artificial intelligence in curriculum integration: opportunities, concerns, and professional development needs. *Frontiers in Artificial Intelligence*, *9*, 1806165. https://doi.org/10.3389/frai.2026.1806165

Kohnke, L., & Zou, D. (2025). The role of ChatGPT in enhancing English teaching. *Educational Technology & Society*, *28*(3), 4-20.

Korchak, A., Al Murshidi, G., Getman, A., Raouf, N., Arshe, M., Al Meheiri, N., Shulgina, G., & Costley, J. (2025). The role of social influence in generative artificial intelligence ChatGPT adoption intentions among undergraduate and graduate students. *Innovations in Education and Teaching International*, *62*(5), 1559-1573. https://doi.org/10.1080/14703297.2025.2496942

Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: A practical primer for t-tests and ANOVAs. *Frontiers in Psychology, 4*, 863. https://doi.org/10.3389/fpsyg.2013.00863

Li, M., & Wang, Y. (2024). Gender and technology adoption in education: A meta-analysis of post-pandemic studies. *Computers in Human Behavior, 150*, 107987. https://doi.org/10.1016/j.chb.2023.107987

Linus, A., Aladesusi, G., Ishola, A., & Elizabeth, F. (2025). Perceived Usefulness, Ease of Use, And Intention to Utilize Online Tools for Learning Among College of Education Students. *Indonesian Journal of Multidiciplinary Research*, *5*, 41-52. https://doi.org/10.17509/ijomr.v5i1.81387

Liu, Q., Jiang, X., & Jiang, R. (2025). Classroom Behavior Recognition Using Computer Vision: A Systematic Review. *Sensors*, *25*, 373. https://doi.org/10.3390/s25020373

Miao, F., & Cukurova, M. (2024). *UNESCO AI competency framework for teachers*. https://doi.org/10.54675/ZJTE2084

Mishara, P. (2024). The Ethical Implications of AI in Education: Privacy, Bias, and Accountability. *Journal of Informatics Education and Research*, *4*(2),1287. https://doi.org/10.52783/jier.v4i2.1827

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, *108*(6), 1017-1054.

Mohamed, M. G., Goktas, P., Khalaf, S. A., Kucukkaya, A., Al-Faouri, I., Seleem, E. A. E. S., Ibraheem, A., Abdelhafez, A. M., Abdullah, S. O., & Zaki, H. N. (2025). Generative artificial intelligence acceptance, anxiety, and behavioral intention in the middle east: a TAM-based structural equation modelling approach. *BMC Nursing*, *24*(1), 703.

Morgan, K., Garay, S., Reed, H., de Vocht, F., & Murphy, S. (2024). Factors underpinning the adoption of a school-based growth mindset intervention: a qualitative study. *Educational Psychology in Practice*, *40*(4), 509-530. https://doi.org/10.1080/02667363.2024.2414455

Moundridou, M., Matzakos, N., & Doukakis, S. (2024). Generative AI tools as educators' assistants: Designing and implementing inquiry-based lesson plans. *Computers and Education: Artificial Intelligence*, *7*, 100277. https://doi.org/10.1016/j.caeai.2024.100277

Nazaretsky, T., Mejia-Domenzain, P., Swamy, V., Frej, J., & Käser, T. (2025). The critical role of trust in adopting AI-powered educational technology for learning: An instrument for measuring student perceptions. *Computers and Education: Artificial Intelligence*, *8*, 100368. https://doi.org/10.1016/j.caeai.2025.100368

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, *2*, 100041.

Nguyen, A., Kishore, S., Hong, Y., Qutab, S., & Dang, B. (2025). Generative Artificial Intelligence (AI) in education: from organizing visions to official guidelines. *Information Technology & People*, *38*(8), 172-199. https://doi.org/10.1108/ITP-08-2024-1026

Ning, Y., Zhang, C., Xu, B., Zhou, Y., & Wijaya, T. (2024). Teachers' AI-TPACK: Exploring the Relationship between Knowledge Elements. *Sustainability*, *16*, 978. https://doi.org/10.3390/su16030978

Nurtanto, M., Nawanksari, S., Sutrisno, V. L. P., Syahrudin, H., Kholifah, N., Rohmantoro, D., Utami, I. S., Mutohhari, F., & Hamid, M. A. (2025). Determinants of behavioral intentions and their impact on student performance in the use of AI technology in higher education in Indonesia: A SEM-PLS analysis based on TPB, UTAUT, and TAM frameworks. *Social Sciences & Humanities Open*, *11*, 101638. https://doi.org/10.1016/j.ssaho.2025.101638

Pandey, R. (2024). Advancing Teacher Education: A Holistic Approach Across Primary, Secondary, and Higher Levels. *Management*, *7*(2), 22-30.

Peñarroja, V., Sanchez, J., Gamero, N., Orengo, V., & Abad, A. (2019). The influence of organisational facilitating conditions and technology acceptance factors on the effectiveness of virtual communities of practice. *Behaviour & Information Technology*, *38*, 1-13. https://doi.org/10.1080/0144929X.2018.1564070

Prilop, C. N., Mah, D.-K., Jacobsen, L. J., Hansen, R. R., Weber, K. E., & Hoya, F. (2025). Generative AI in teacher education: Educators' perceptions of transformative potentials and the triadic nature of AI literacy explored through AI-enhanced methods. *Computers and Education: Artificial Intelligence*, *9*, 100471. https://doi.org/10.1016/j.caeai.2025.100471

Romadhon, I. A., Nofirman, N., Meliza, A., Susanti, M. M. I., & Asbaruna, L. W. B. (2025). Classroom teacher strategies for fostering digital literacy awareness in elementary students: A literature review. *Journal of Innovation and Research in Primary Education*, *4*(3), 966-976.

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, *128*, 13-35. https://doi.org/10.1016/j.compedu.2018.09.009

Schmidt, D. A., Baran, E., Thompson, A. D., Mishra, P., Koehler, M. J., & Shin, T. S. (2009). Technological Pedagogical Content Knowledge (TPACK). *Journal of Research on Technology in Education*, *42*(2), 123-149. https://doi.org/10.1080/15391523.2009.10782544

Shi, D., Lee, T., & Maydeu-Olivares, A. (2019). Understanding the Model Size Effect on SEM Fit Indices. *Educational Psychological Measurement*, *79*(2), 310-334. https://doi.org/10.1177/0013164418783530

Shi, J. (2024). A Comparative Study of China and U.S.: The Influence of Digital Divide on Education Inequality and Its Mitigating Policies. *Lecture Notes in Education Psychology and Public Media*, *64*, 9-20. https://doi.org/10.54254/2753-7048/64/20240937

Shi, W., Li, L., Zhang, Z., Li, M., & Li, J. (2025). Research on driving factors of consumer purchase intention of artificial intelligence creative products based on user behavior. *Scientific Reports*, *15*(1), 17400. https://doi.org/10.1038/s41598-025-01258-x

Sun, Q., Jin, F., & Li, L. (2026). Determinants of perceived usefulness, satisfaction and behavioral intention of using AI in lesson planning among English teachers. *Frontiers in Psychology*, *17*, 1732508. https://doi.org/10.3389/fpsyg.2026.1732508

Taheri, R., Nazemi, N., Pennington, S. E., Clark, J. A., & Dadgostari, F. (2025). Factors influencing educators' AI adoption: A grounded meta-analysis review. *Computers and Education: Artificial Intelligence*, *9*, 100464. https://doi.org/10.1016/j.caeai.2025.100464

Tan, X., Cheng, G., & Ling, M. H. (2025). Artificial intelligence in teaching and teacher professional development: A systematic review. *Computers and Education: Artificial Intelligence*, *8*, 100355.

Tashtoush, M. A., Wardat, Y., Ali, R. A., & Saleh, S. (2024). Artificial intelligence in education: mathematics teachers' perspectives, practices and challenges. *Iraqi Journal for Computer Science and Mathematics*, *5*(1), 20.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *Int J Med Educ*, *2*, 53-55. https://doi.org/10.5116/ijme.4dfb.8dfd

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS Quarterly*, *27*(3), 425-478.

Wang, J., Tigelaar, E., & Admiraal, W. (2022). From policy to practice: integrating ICT in Chinese rural schools. *Technology Pedagogy and Education*, *31*, 509-524. https://doi.org/10.1080/1475939X.2022.2056504

Wang, Y. A., & Rhemtulla, M. (2021). Power Analysis for Parameter Estimation in Structural Equation Modeling: A Discussion and Tutorial. *Advances in Methods and Practices in Psychological Science*, *4*(1), 2515245920918253. https://doi.org/10.1177/2515245920918253

Wulandari, P. (2022). Structural Equation Modelling (SEM) in Research: Narrative Literature Review. *Open Access Indonesia Journal of Social Sciences*, *5*, 852-858. https://doi.org/10.37275/oaijss.v5i6.141

Xu, S., Chen, P., & Zhang, G. (2024). Exploring Chinese University Educators' Acceptance and Intention to Use AI Tools: An Application of the UTAUT2 Model. *SAGE Open*, *14*(4), 21582440241290013. https://doi.org/10.1177/21582440241290013

Yan Yan, C., & Jafri, N. B. (2026). Factors influencing the intention to use generative artificial intelligence in educational systems: a meta-analysis. *BMC Psychology*, *14*(1), 308. https://doi.org/10.1186/s40359-026-03957-0

Yang, F.-C. (2026). Factors influencing K–12 teachers' intention to adopt AI tools in teaching: Extending TAM with AI tool competence and school support. *Education and Information Technologies*,1-35. https://doi.org/10.1007/s10639-026-14040-x

Yu, M. (2025). An AI-driven tools assessment framework for english teachers using the Fuzzy Delphi algorithm and deep learning. *Scientific Reports*, *15*(1), 41531. https://doi.org/10.1038/s41598-025-25466-7

Zhang, D., Fu, G., Cao, K., Wang, X., & Li, H. (2026). Trust and heterogeneity in GAI adoption: an integrated TAM–UTAUT–trust model among Chinese K− 12 teachers. *Frontiers in Education, 11,*1825053.

Zhang, J., Liu, Q., & Sun, Y. (2023). Teachers' acceptance of artificial intelligence in education: Evidence from Chinese primary schools. *Education and Information Technologies, 28*(9), 11245–11267. https://doi.org/10.1007/s10639-023-11678-2

Zhang, N., Wong, W. L., & Barrot, J. (2025). Primary teachers' acceptance and sustained adoption of AI powered learner corpora for writing instruction through TAM and ECM perspectives. *Scientific Reports*, *15*(1), 37399. https://doi.org/10.1038/s41598-025-21205-0

Zhao, D.-Q., Yu, L., Che, Z.-Y., & Wu, L.-K. (2024). Re-understanding of UTAUT in Teachers' Technology Adoption Research——Based on Quantitative Comprehensive Analysis of One-stage Meta-analysis Structural Equation Modeling. *Modern Educational Technology*, *34*(9), 48-58.

Zhao, J., Li, S., & Zhang, J. (2025). Understanding teachers' adoption of AI technologies: An empirical study from Chinese middle schools. *Systems*, *13*(4), 302.

Zou, D., Xie, H., & Kohnke, L. (2025). Navigating the future: establishing a framework for educators' pedagogic artificial intelligence competence. *European Journal of Education*, *60*(2), e70117.



APPENDIXES



APPENDIX A

Questionnaire

Appendix A : Questionnaire (English Version)

A Questionnaire Survey on the Influencing Factors of Primary School Teachers' Use of Artificial Intelligence Teaching Tools

Questionnaire Instructions

Dear respondent:

Thank you for taking part in this survey. This questionnaire aims to explore the influencing factors of primary school teachers' intention to use of AI-assisted teaching tools. Your responses will be used solely for academic research purposes, and all information will be strictly confidential. Please feel free to complete the survey. It is estimated that the process will take approximately 5 to 8 minutes. We appreciate your support and cooperation!

Filling instructions: Please answer based on your actual situation.

Part 1: Basic Information

Fill in or select based on your actual situation.

1. What is your gender?

☐ Male ☐ Female

2. How old are you?

☐ Under 25 years of age

☐ 26 to 35 years old

☐ 36 to 44 years old

☐ 45-54 years old

☐ 55 years of age and older

3. Years of teaching:

☐ 0-3 years

☐ 4-7 years

☐ 8-15 years

☐ 16–25 years

☐ 26 years or older

4. Highest Education:

☐ junior college

☐ undergraduate course

☐ Master

☐ doctor

5. Professional Title:

☐ Not graded

☐ Secondary Teacher

☐ First-level Teacher

☐ a senior teacher

☐ Senior Teacher

6. Subjects to teach (multiple selections allowed):

☐ Chinese

☐ mathematics

☐ English

☐ science

☐ information technology

☐ Music, Physical Education, and Art

☐ Others _____

7. School location:

☐ Main urban area of a provincial capital/municipality directly under the central government

☐ Prefecture-level city districts

☐ County/city at the county level

☐ Township/Rural

8. School Type:

☐ Public primary school

☐ civilian-run primary school

A. 1 Part 2: Performance Expectancy (PE)

Please select the option that best reflects your true feelings (1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree).

Title	1	2	3	4	5
PE1: I would find the system useful in my job.					
PE2: Using the system enables me to accomplish tasks more quickly.					
PE3: Using the system increases my productivity.					
PE4: If I use the system, I will increase my chances of getting a raise.					

A. 2 Part 3: Effort Expectancy (EE)

Title	1	2	3	4	5
EE1: My interaction with the system would be clear and understandable.					
EE2: It would be easy for me to become skillful at using the system.					
EE3: I would find the system easy to use.					
EE4: Learning to operate the system is easy for me.					

A. 3 Part IV: Social influence (SI)

Title	1	2	3	4	5
SI1: People who influence my behavior think that I should use the system.					
SI2: People who are important to me think that I should use the system.					
SI3: The senior management of this business has been helpful in the use of the system.					

A. 4 Part V: Facilitating Conditions (FC)

Title	1	2	3	4	5
FC1: I have the resources necessary to use the system.					
FC2: I have the knowledge necessary to use the system.					
FC3: The system is not compatible with other systems I use. (R)					
FC4: A specific person (or group) is available for assistance with system difficulties.					

A. 5 Part VI: I-TPACK Competencies (TPACK)

Title	1	2	3	4	5
TPACK1: I can teach lessons that appropriately combine my subject matter, technologies and teaching approaches.					
TPACK2: I can select technologies to use in my classroom that enhance what I teach, how I teach and what students learn.					
TPACK3: I can use strategies to combine content, technologies and teaching approaches in my classroom.					

A. 6 Part VII: Intention to Use AI Teaching Tools (INT)

Title	1	2	3	4	5
INT1: I intend to use the system in the next months.					
INT2: I predict I would use the system in the next months.					
INT3: I plan to use the system frequently.					

Appendix B : Questionnaire (Chinese Version)

小学教师使用人工智能教学工具的影响因素问卷调查

问卷填写说明

尊敬的受访者：

诚邀您参与本研究的问卷填写。本研究主要考察小学教师使用人工智能教学工具的意愿及其影响因素，并期望通过调查结果为此类工具在基础教育情境中的合理应用提供实证参考。

本次调查所得资料仅服务于本研究。问卷不收集可识别个人身份的信息，相关资料将得到妥善保护，且不会作商业用途。完成全部题目预计需要 5－8 分钟。作答过程中，请结合您个人的实际经历与判断选择相应答案。您的反馈对本研究具有重要价值。

衷心感谢您的参与和支持！

填写说明：请结合个人实际情况，在相应选项处勾选（√）。

第一部分：基本信息

根据您的实际情况填写或选择。

1. 性别：

☐ 男 ☐ 女

2. 年龄：

☐ 25 岁及以下

☐ 26–35 岁

☐ 36–44 岁

☐ 45–54 岁

☐ 55 岁及以上

3. 您的教龄是：

☐ 0-3 年

☐ 4-7 年

☐ 8-15 年

☐ 16 - 25 年

☐ 26 年及以上

4. 您的最高学历：

☐ 大专

☐ 大学本科

☐ 硕士

☐ 博士

5. 您目前的教师职称是：

☐ 未评职称

☐ 一级教师

☐ 二级教师

☐ 高级教师

☐ 正高级教师

6. 您目前任教的学科（可多选）：

☐ 语文

☐ 数学

☐ 英语

☐ 科学

☐ 信息技术

☐ 音乐，体育教育，艺术

☐ 其他 _____

7. 学校所在地：

☐ 省会城市或直辖区主城区

☐ 地级市城区

☐ 县级行政区（县级市）

☐ 城镇/农村地区

8. 学校类型：

☐ 公立小学

☐ 民办小学

B.1 第二部分：绩效预期（PE）

请选择最能反映您真实感受的选项（1=强烈不同意，2=不同意，3=中立，4=同意，5=强烈同意）。

题项	1	2	3	4	5
PE1：我认为人工智能教学工具对我的教学工作具有实际帮助。					
PE2：使用人工智能教学工具可使我更快速地完成各项任务。					
PE3：使用人工智能教学工具显著提升了我的工作效率。					
PE4：使用人工智能教学工具能够提升我的教学绩效。					

B.2 第三部分：努力预期（EE）

题项	1	2	3	4	5
EE1：我与人工智能教学工具的操过程清晰易懂。					
EE2：我能够较容易掌握人工智能教学工具的使用方法。					
EE3：我认为人工智能教学工具易于使用。					
EE4：对我而言，学习使用人工智能教学工具是一件容易的事情。					

B.3 第四部分：社会影响（SI）

题项	1	2	3	4	5
SI1. 对我有影响的人认为我应该使用人工智能教学工具。					
SI2. 对我而言重要的人支持我使用人工智能教学工具。					
SI3. 学校管理者（如校长或学校领导）鼓励教师使用人工智能教学工具。					

B.4 第五部分：促进条件（FC）

题项	1	2	3	4	5
FC1. 我具备使用人工智能教学工具所需的资源(如设备、网络等)。					
FC2. 我具备使用人工智能教学工具所需的知识和技能。					
FC3. 人工智能教学工具与我目前使用的教学系统之间存在兼容性问题。（反向题）					
FC4. 当我在使用人工智能教学工具时，能够获得相关人员或技术支持团队的帮助。					

B.5 第六部分：I- TPACK 能力（TPACK）

题项	1	2	3	4	5
TPACK1. 我能够将学科知识、人工智能教学工具和教学方法有效结合开展课堂教学。					
TPACK2. 我能够选择适合课堂教学的人工智能教学工具，以提升教学内容、教学方法和学生学习效果。					
TPACK3. 我能够灵活运用不同教学策略，将学科内容、人工智能教学工具和教学方法有效整合。					

B.6 第七部分：使用人工智能教学工具（INT）的意图

题项	1	2	3	4	5
INT1. 我计划在今后的教学工作中使用人工智能教学工具。					
INT2. 我预计自己将在今后的教学工作中持续使用人工智能教学工具。					
INT3. 我计划经常使用人工智能教学工具辅助教学。					

APPENDIX B

Article

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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

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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

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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-

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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.

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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.

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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

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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

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proposed:

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

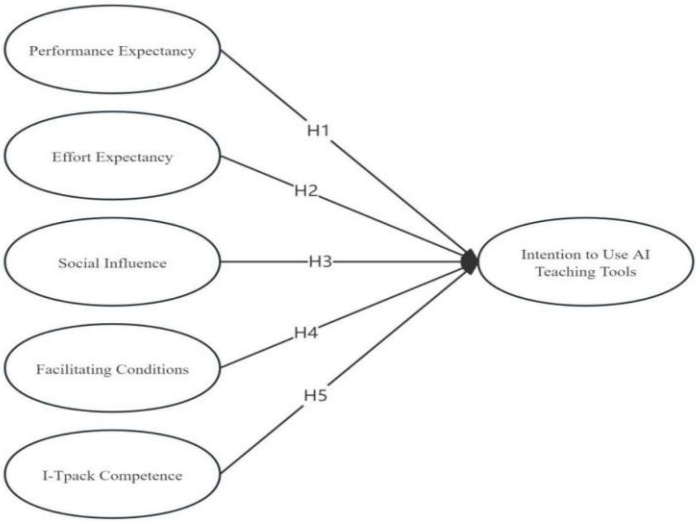


Figure 1. Conceptual model

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

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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

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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,

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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.

 DOI: *10.5281/zenodo.21236291*

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

 DOI: *10.5281/zenodo.21236291*

	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.

 DOI: *10.5281/zenodo.21236291*

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

 DOI: *10.5281/zenodo.21236291*

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

 DOI: *10.5281/zenodo.21236291*

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; *** $p < 0.001$.

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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

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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

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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.

 DOI: *10.5281/zenodo.21236291*

References

2. An, X., Chai, C. S., Li, Y., Zhou, Y., Shen, X., Zheng, C., & Chen, M. (2023). Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. *Education and Information Technologies*, *28*(5), 5187-5208. https://doi.org/10.1007/s10639-022-11286-z

3. Ayanwale, M. A., Sanusi, I. T., Adelana, O. P., Aruleba, K. D., & Oyelere, S. S. (2022). Teachers' readiness and intention to teach artificial intelligence in schools. *Computers and Education: Artificial Intelligence*, *3*, 100099. https://doi.org/10.1016/j.caeai.2022.100099

4. Celik, I. (2023). Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. *Computers in Human Behavior*, *138*, 107468. https://doi.org/10.1016/j.chb.2022.107468

5. Chanda, R., Vafaei-Zadeh, A., Hanifah, H., & Ramayah, T. (2025). Artificial intelligence teaching assistant adoption in university education: Key drivers through the ability, motivation and opportunity framework. *Education and Information Technologies*, *30*, 14123-14164. https://doi.org/10.1007/s10639-025-13360-8

6. Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.2307/3151312

7. Hazzan-Bishara, A., Kol, O., & Levy, S. (2025). The factors affecting teachers' adoption of AI technologies: A unified model of external and internal determinants. *Education and Information Technologies*, *30*(11), 15043-15069. https://doi.org/10.1007/s10639-025-13393-z

8. Howard, M., Boudreaux, M., & Oglesby, M. (2024). Can Harman's single-factor test reliably distinguish between research designs? Not in published management studies. *European Journal of Work and Organizational Psychology*, *33*, 1-15. https://doi.org/10.1080/1359432X.2024.2393462

9. Hussey, I., Alsalti, T., Bosco, F., Elson, M., & Arslan, R. (2025). An Aberrant

 DOI: *10.5281/zenodo.21236291*

Abundance of Cronbach's Alpha Values at .70. *Advances in Methods and Practices in Psychological Science*, *8*(1), 25152459241287123. https://doi.org/10.1177/25152459241287123

10. Kalawati, Sahu, S., & Swamy, N. K. (2026). Factors influencing teachers' adoption of artificial intelligence tools in K-12 education. *International Journal of Applied Resilience and Sustainability*, *2*, 943-965. https://doi.org/10.70593/deepsci.0202039

11. Kayalı, B., Balat, Ş., & Yavuz, M. (2026). Examining the relationships between artificial intelligence literacy, AI-TPACK, job satisfaction, and well-being among teachers through structural equation modeling. *Acta psychologica*, *268*, 107297. https://doi.org/10.1016/j.actpsy.2026.107297

12. Kayıran, D., Sönmez, M., Avcı, A., & Haji Mohamud, R. Y. (2026). Teachers' perceptions of artificial intelligence in curriculum integration: opportunities, concerns, and professional development needs. *Frontiers Artificial Intelligence*, *9*, 1806165. https://doi.org/10.3389/frai.2026.1806165

13. Kic-Drgas, J., & Kılıçkaya, F. (2026). Artificial Intelligence Tool Adoption for Teachers' Self-Regulated Learning: A Qualitative Study of In-Service Language Teachers. *SAGE Open*, *16*(2), 21582440261447078. https://doi.org/10.1177/21582440261447078

14. Kline, R. B. (2024). How to evaluate local fit (residuals) in large structural equation models. *International Journal of Psychology*, *59*(6), 1293-1306. https://doi.org/10.1002/ijop.13252

15. Li, H., Chai, C. S., & Wang, X. (2025). Promoting pre-service music teachers' TPACK with generative AI: an intervention through designing with AI. *Computers and Education: Artificial Intelligence*, *9*, 100525. https://doi.org/10.1016/j.caeai.2025.100525

16. Li, M. (2025). Exploring the digital divide in primary education: A comparative study of urban and rural mathematics teachers' TPACK and attitudes towards technology integration in post-pandemic China. *Education and Information Technologies*, *30*(2), 1913-1945. https://doi.org/10.1007/s10639-024-12890-x

 DOI: *10.5281/zenodo.21236291*

17. Li, M., & Manzari, E.-E. (2025). AI utilization in primary mathematics education: a case study from a southwestern Chinese city. *Education and Information Technologies*, *30*, 11717-11750. https://doi.org/10.1007/s10639-025-13315-z

18. Lin, R., Chu, J., Yang, L., Lou, L., Yu, H., & Yang, J. (2023). What are the determinants of rural-urban divide in teachers' digital teaching competence? Empirical evidence from a large sample. *Humanities and Social Sciences Communications*, *10*(1), 422. https://doi.org/10.1057/s41599-023-01933-2

19. Mishra, M. (2016). Confirmatory Factor Analysis (CFA) as an Analytical Technique to Assess Measurement Error in Survey Research: A Review. *Paradigm*, *20*, 97-112. https://doi.org/10.1177/0971890716672933

20. Mishra, P., & Koehler, M. J. (2006). Technological Pedagogical Content Knowledge: A Framework for Teacher Knowledge. *Teachers College Record*, *108*(6), 1017-1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x

21. Moschaki, S., Lefkos, I., Neofotistos, V., & Fachantidis, N. (2026). *The Use of Artificial Intelligence (AI) in Primary and Secondary Education: Teachers' Perspectives*. https://doi.org/10.1109/ICAITE68636.2025.11442591

22. Moundridou, M., Matzakos, N., & Doukakis, S. (2024). Generative AI tools as educators' assistants: Designing and implementing inquiry-based lesson plans. *Computers and Education: Artificial Intelligence*, *7*, 100277. https://doi.org/10.1016/j.caeai.2024.100277

23. Oved, O., & Alt, D. (2025). Teachers' technological pedagogical content knowledge (TPACK) as a precursor to their perceived adopting of educational AI tools for teaching purposes. *Education and Information Technologies*, *30*, 14095-14121. https://doi.org/10.1007/s10639-025-13371-5

24. Rana, M. M., Siddiqee, M. S., Sakib, M. N., & Ahamed, M. R. (2024). Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. *Heliyon*, *10*(18), e37569. https://doi.org/10.1016/j.heliyon.2024.e37569

25. Runge, I., Hebibi, F., & Lazarides, R. (2025). Acceptance of Pre-Service Teachers Towards Artificial Intelligence (AI): The Role of AI-Related Teacher Training

 DOI: *10.5281/zenodo.21236291*

Courses and AI-TPACK Within the Technology Acceptance Model. *Education Sciences*, *15*, 167. https://doi.org/10.3390/educsci15020167

26. Schmidt-Crawford, D., Baran, E., Thompson, A., Mishra, P., Koehler, M., & Seob, S. (2009). Technological Pedagogical Content Knowledge (TPACK): The Development and Validation of an Assessment Instrument for Preservice Teachers. *Journal of Research on Technology in Education*, *42*, 123-149. https://doi.org/10.1080/15391523.2009.10782544

27. Taheri, R., Nazemi, N., Pennington, S. E., Clark, J. A., & Dadgostari, F. (2025). Factors influencing educators' AI adoption: A grounded meta-analysis review. *Computers and Education: Artificial Intelligence*, *9*, 100464. https://doi.org/10.1016/j.caeai.2025.100464

28. Taiwo, A., & Downe, A. (2013). The theory of user acceptance and use of technology (UTAUT): A meta-analytic review of empirical findings. *Journal of Theoretical and Applied Information Technology*, *49*, 48-58. https://khub.utp.edu.my/scholars/id/eprint/4027

29. Tan, X., Cheng, G., & Ling, M. H. (2025). Artificial intelligence in teaching and teacher professional development: A systematic review. *Computers and Education: Artificial Intelligence*, *8*, 100355. https://doi.org/10.1016/j.caeai.2024.100355

30. Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User Acceptance of Information Technology: Toward A Unified View1. *MIS Quarterly*, *27*, 425-478. https://doi.org/10.2307/30036540

31. Wang, Y. A., & Rhemtulla, M. (2021). Power Analysis for Parameter Estimation in Structural Equation Modeling: A Discussion and Tutorial. *Advances in Methods and Practices in Psychological Science*, *4*(1), 2515245920918253. https://doi.org/10.1177/2515245920918253

32. Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample Size Requirements for Structural Equation Models: An Evaluation of Power, Bias, and Solution Propriety. *Educational Psychological Measurement*, *76*(6), 913-934. https://doi.org/10.1177/0013164413495237

 DOI: *10.5281/zenodo.21236291*

33. Wu, R., Wang, X., Nie, Y., Lv, P., & Luo, X. (2025). Exploring Factors Influencing Pre-Service Teachers' Intention to Use GenAI for Instructional Design: A Grounded Theory Study. *Behavioral Sciences*, *15*(9),1169. https://doi.org/10.3390/bs15091169

34. Xu, S., Chen, P., & Zhang, G. (2024). Exploring Chinese University Educators' Acceptance and Intention to Use AI Tools: An Application of the UTAUT2 Model. *SAGE Open*, *14*(4),21582440241290013. https://doi.org/10.1177/21582440241290013

35. Yan, Y., Liu, H., & Chau, T. (2025). A Systematic Review of AI Ethics in Education. *Journal of Global Information Management*, *33*(1),1-50. https://doi.org/10.4018/JGIM.386381

36. Yang, F.-C. (2026). Factors influencing K–12 teachers' intention to adopt AI tools in teaching: Extending TAM with AI tool competence and school support. *Education and Information Technologies,26*,1-35. https://doi.org/10.1007/s10639-026-14040-x

37. Yang, Y., Xia, Q., Liu, C., & Chiu, T. K. F. (2025). The impact of TPACK on teachers' willingness to integrate generative artificial intelligence (GenAI): The moderating role of negative emotions and the buffering effects of need satisfaction. *Teaching and Teacher Education*, *154*, 104877. https://doi.org/10.1016/j.tate.2024.104877

38. Yim, I., & Su, J. (2025). Artificial intelligence literacy education in primary schools: a review. *International Journal of Technology and Design Education*, *35*, 2175-2204. https://doi.org/10.1007/s10798-025-09979-w

39. Zhang, X., & Wareewanich, T. (2024). A Study of the Factors Influencing Teachers' Willingness to Use Generative Artificial Intelligence Based on the UTAUT Model. *International Journal of Interactive Mobile Technologies (IJIM)*, *18*, 126-142. https://doi.org/10.3991/ijim.v18i06.47991

40. Zhao, W. (2024). A study of the impact of the new digital divide on the ICT competences of rural and urban secondary school teachers in China. *Heliyon*, *10*, e29186. https://doi.org/10.1016/j.heliyon.2024.e29186

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