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A Study of the Internal and External Factors Influencing the Adoption of Artificial Intelligence by Elementary School Math Teachers

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Abstract

The variables impacting the adoption and use of Artificial Intelligence (AI) in elementary mathematics education are thoroughly examined in this research. The study uses a quantitative research approach and incorporates empirical data obtained from Chinese primary mathematics instructors using the Technology Acceptance Model (TAM) and Technological Pedagogical and Content Knowledge (TPACK). Teacher attitudes, contextual variables, educational obstacles, family and community participation, and other relevant dimensions are examined via the use of Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that there is a strong correlation between teacher attitudes and the adoption of AI. By narrowing down on AI in elementary math education, this research adds to the body of knowledge on the topic and calls attention to the need for strategic professional development programs to improve teachers' comfort with and competence using AI tools. Furthermore, the study highlights the importance of TPACK via its crucial function in providing educators with the expertise needed to successfully incorporate AI into mathematics curricula. In addition, the research delves into the intricate interplay between AI integration and contextual variables and educational hurdles, highlighting the need of systemic measures that include governmental shifts and institutional backing. We also take a look at the indirect channels by which TPACK influences AI use, as well as the role of parents and the community, to provide light on the complex nature of technology adoption in schools. Educators, legislators, and stakeholders may benefit from its practical consequences, and it adds to the intellectual conversation on technology integration in education.

Keywords: AI, elementary math instruction, teacher mindsets, technology, problem-solving, and knowledge (TPACK) in the classroom

Introduction

The age after a pandemic is a pivotal one for incorporating technology, especially AI, into educational institutions throughout the world (Hofer et al., 2021). The importance of digital technology in education was highlighted by the transition to remote and hybrid learning models during the global health crisis. Tools that can analyze student involvement, performance, and preferences to promote individualized learning have been made possible by AI, which has significantly increased teaching and learning techniques (Kim & Lee, 2023). Dermeval et al. (2017) found that AI teaching systems in elementary mathematics were very useful for spotting students' mistakes and giving them fast feedback, which helped them understand the material better. In mathematics education, intelligent tutoring systems are currently crucial for individualized learning plans, result prediction, and resource recommendation (Shin, 2022). As an example, AI may assist educators by recognizing which pupils are having difficulty and providing them with individualised assistance (Qiu et al., 2023). Therefore, in the post-pandemic age, artificial intelligence (AI) has become more than just a technological add-on; it has become an integral element of the educational process.

AI in Chinese Primary Mathematics Education

According to Knox (2020) and Yang (2019), the use of artificial intelligence in elementary schools in China is rapidly expanding. AI-powered resources like Baidu's Ernie Bot, Qwen, and Khan Academy are included into elementary mathematics curricula. Intelligently interacting with educators and students, these AI tools answer mathematical issues, and use advanced machine learning and natural language processing technology (Yi et al., 2024). Yoon et al. (2024) cite many examples of generative AI, such as Ernie Bot and ChatGPT, that analyze student performance data and modify educational content to suit individual requirements in order to create individualized learning experiences. Using Ernie Bot, math instructors in a regular classroom may create individualized arithmetic homework for their students that takes into account their current skill level and learning rate. Intelligent coaching is also available via adaptive learning systems like Khan Academy, which provide detailed explanations and answers to mathematical problems (Shin, 2022). Students benefit from this individualized instruction since it clarifies difficult ideas and frees up instructors to concentrate on areas where their students need it most (Yi et al., 2024).

The use of intelligent systems and technologies to improve teaching and learning processes is referred to as AI tools in primary mathematics education in this research. Examples of such tools include adaptive learning systems like Khan Academy and generative AI tools like Ernie Bot and ChatGPT. Some examples of this kind of application include intelligent tutoring, virtual experiments, personalized learning, and real-time assessment and feedback; and personalized experiments. Here, we look at how AI technologies may enhance primary school math instruction by providing kids with personalized, engaging, and productive learning experiences.

Problem Statement

Primary mathematics education, in particular in China's educational system, is only just beginning to incorporate AI into its teaching practices, despite the technology's obvious benefits and revolutionary potential (Yang, 2019). Internal obstacles include teachers' varied degrees of Technological Pedagogical Content Knowledge (TPACK) and their unfavorable attitudes towards the usage of technology. Contextual factors (CF) make these problems worse. Examples of CF include uneven school infrastructure, lack of technology, inconsistent institutional policies, inconsistent levels of administrative support, and insufficient resources. This is especially true in rural or underserved areas, where math teachers may not have the same support or confidence as their urban counterparts (Bakker et al., 2021; Zhao, 2024). As an example, it is challenging for instructors in rural schools to get enough training and support, which in turn hampers their capacity to incorporate digital technologies into their teaching practices and make good use of them (Wu et al., 2022). Further complicating AI integration are educational difficulties (EC), such as the need to provide substantial teacher training and the difficulty of integrating AI technology with current curriculum. Indeed, according to Whitney-Smith (2023), in order for AI technologies to be integrated effectively, they must be properly matched with learning goals and evaluation processes. To get there, educators need a lot of help understanding and using AI-based lessons (Sperling et al., 2022). Opportunities for professional development and materials to assist educators in incorporating AI into their teaching practices are part of this assistance. Rigid curriculum requirements and conventional evaluation techniques might hinder the implementation of new technology-driven teaching approaches in China's highly organized educational system. Additionally, in the post-pandemic age, PCI (parental and community engagement) is crucial for the effective incorporation of AI into elementary mathematics curricula. The importance of parental and community involvement in bolstering online and tech-enhanced education has been brought to light by the COVID-19 epidemic. Their buy-in is critical for the successful use of AI tools in the classroom. Whether parents embrace technology and help their children learn at home may have a big impact on how AI is used in the classroom (Chen, 2015). According to Tay et al. (2021), digital technology adoption may be accelerated by community participation and support for educational innovation. On the other side, artificial intelligence programs may fail to take off and remain strong if they do not have the backing of parents and the society at large. The uneven support for AI integration in China is a result of regional differences in parental and community participation, which further complicates attempts to properly adopt these technologies.
In light of these complex issues, this research seeks to examine the impact of internal (mathematics teachers' attitudes and TPACK) and external (CF, EC, and PCI) elements on the implementation of AI in Chinese primary mathematics education. Improving primary school mathematics instruction for students requires an understanding of the interplay between these elements in order to design interventions and methods to assist instructors make good use of AI technologies. The process begins with the formulation of a significant research topic that will serve as the investigation's compass.

- How do internal factors such as teacher attitudes and TPACK, and external fac- tors including CF, EC, and PCI, influence the adoption of AI in primary math- ematics education?

Literature Review

TPACK and TAM in Primary Mathematics Education

The complicated integration of digital technology in mathematics education may be better understood via the lenses of the Technology Acceptance Model (TAM) and the Theory of Competences for Knowledge (TPACK) in the modern era of education (Joo et al., 2018; Mai-lizar et al., 2021). Shulman's (1986) Pedagogical Content Knowledge theory served as the theoretical foundation for TPACK, which stresses the significance of comprehending not just the interplay between technology, pedagogy, and content, but also these three areas independently (Mishra & Koehler, 2006). In contrast, the Technology Acceptance Model (TAM) postulates that people's views about the practicality and simplicity of technology are the most important factors in their decision to employ it (Davis, 1989). According to Mailizar et al. (2021), TPACK and TAM provide thorough viewpoints on how technology is integrated into mathematical education.
According to Koh (2018) and Kurt and Çakıroğlu (2023), the TPACK framework has had a significant impact on how digital technology is used in mathematics teaching. According to Mishra & Koehler (2006) and Mishra et al. (2023), this paradigm highlights the need of combining technical expertise with pedagogical and subject knowledge in order to develop more successful techniques for teaching. According to Li et al. (2024), the TPACK framework is commonly used in five main areas of primary mathematics education: curriculum planning, assessment formulation, evaluating teacher educational initiatives, and professional advancement program design. One study that looked at how math instructors used TPACK principles to include technology into geometry lessons is Ibili et al. (2019). The use of graphing software in their research enhanced the learning experience by allowing students to dynamically alter shapes and measure angles (Ibili et al., 2019). This proves that by using the TPACK framework, teachers are able to examine and reflect on their work, leading to a more thorough incorporation of technology that improves instructional methods and helps elementary school students grasp mathematical ideas (Koh et al., 2016). The TPACK framework offers a thorough method for assessing and enhancing math educators' AI integration abilities, making it an ideal choice for this project.
Perceived utility (PU) and perceived ease of use (PEoU) are the two most important aspects of TAM (Davis, 1989; Davis et al., 1989). According to research (Eickelmann & Vennemann, 2017; Gurer, 2021), these factors have a major impact on educators' propensity to use and perceptions of digital tools in the classroom. For instance, Teo (2011) examined the impact

of five critical elements on teachers' desire to use technology using the TAM: PU, PEoU, subjective norms, enabling situations, and attitudes. According to Teo (2011), the research found that among instructors' favorable attitudes towards incorporating technology into their teaching methods, PU and PEoU were the most important. According to several studies (Gurer, 2021; Ibili et al., 2019; Mailizar et al., 2021; Teo et al., 2008), PEoU and PU are strong indicators of how instructors feel about using technology in the classroom. To supplement the insights obtained from the TPACK framework, TAM offers a strong framework for analyzing the elements that impact primary mathematics educators' attitudes and intents towards using AI technologies into their lessons. Consequently, TAM is extremely pertinent to this research. According to Joo et al. (2018) and Mailizar et al. (2021), a comprehensive view of how digital technology is being used in mathematics education may be gained by combining the TPACK and TAM frameworks. In order to help teachers implement effective practices, TPACK provides a holistic perspective on the interplay between technical, pedagogical, and subject knowledge (Mishra et al., 2023). Also, TAM supplements this by looking at how educators feel about deploying AI technologies in the classroom (Khong et al., 2023). This research investigates the impact of the knowledge dimensions (TPACK) and the attitudinal dimensions (TAM) on the incorporation of AI in basic mathematics instruction by merging both frameworks. In particular, these two ideas allow the researcher to delve into the ways in which teachers' evaluations of technology's utility and user-friendliness, together with their skill in combining technology with pedagogy and subject knowledge, influence their use of AI tools in the classroom. Because of this symbiotic connection, we can examine the variables that help or hurt the use of AI technologies in elementary school arithmetic lessons with more detail.

External Factors in AI Integration for Primary Mathematics Education

Hew and Brush (2007) noted that CF, such as institutional support, cultural attitudes towards technology, and resource availability, are critical factors in the integration of digital tools in education. Similarly, Koh (2018), Ortmer and Ottenbreit-Leftwich (2010), and Vongkulluksn et al. (2018) all highlighted the importance of CF in education policy. Success or failure of technology integration initiatives is heavily dependent on these elements, which have been the subject of thorough examination in the aforementioned studies. Schools that had strong technical infrastructure and administrative support were better able to integrate digital technology into their lessons, according to research by Tondeur et al. (2017). The difference in technology integration across different educational contexts is especially evident in schools that lack enough resources or administrative support, which makes it difficult for them to properly deploy such technologies. Adopting and effectively using AI systems in elementary mathematics education is greatly influenced by contextual variables, which is why knowing these elements is essential for this research.
When it comes to incorporating digital technologies into the classroom, prior studies have also highlighted the significance of EC. The adoption of novel, technology-driven teaching techniques may be impacted by EC variables such as the conventional evaluation systems, school norms, and the strictness of curricular requirements (Ertmer et al., 2012). One example is the work of Pellegrino and Quellmalz (2010), who argued that high-stakes evaluations may be made more accurate and fair by using technological tools. Furthermore, Chou et al. (2024) discovered that when tertiary professors implement AI technologies, it is crucial for them to collaborate with colleagues, have competent leadership, and adhere to the school's innovation philosophy. Educators of mathematics still face a formidable obstacle in the post-pandemic age when it comes to making good use of AI for this goal. Since these EC are essential variables determining the successful implementation of AI technologies in elementary mathematics instruction, it is crucial that this research comprehend them.
Aside from AI itself, PCI is a major component in how well AI is used in classrooms. Much depends on how the community at large feels about and supports schools' use of technology (Lawrence & Fakuade, 2021). During the COVID-19 epidemic, a study conducted by del Olmo-Muñoz et al. (2023) discovered that the efficacy of incorporating technology into classrooms was greatly affected by the favorable views of both the community and parents towards technology. In their view, the efficacy of integrating technology into the classroom may be enhanced if communities and parents have a favorable view of technology, and if teachers are more likely to embrace and use emerging technologies like AI (del Olmo-Muñoz et al., 2023). Students in elementary school mathematics may benefit from the use of digital technologies like AI if their communities and parents are open to incorporating these innovations into the classroom (Lawrence & Fakuade, 2021). By bringing attention to PCI, we can show how important it is for educators, parents, and the community at large to work together to improve primary mathematics education via the use of artificial intelligence (AI) technologies.

Research Gaps

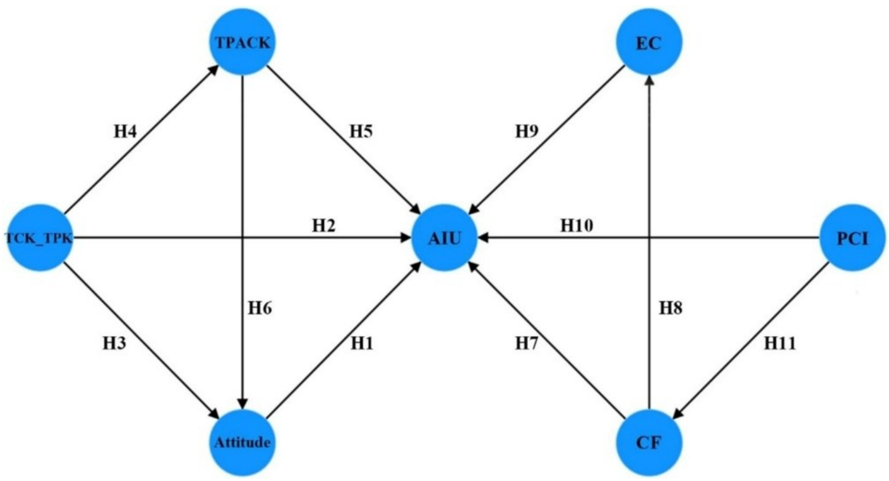
As we've seen, there are a lot of moving parts when it comes to using AI in elementary math classes. External variables like CF, EC, and PCI are just as important as internal ones like TPACK and attitudes. The benefits and drawbacks of using AI in elementary math teaching may be better understood if these factors are considered. However, the interplay of variables such as TPACK, instructor attitudes, CF, EC, and PCI is often neglected in the present body of research. This disparity is most noticeable in elementary school mathematics programs, where the successful incorporation of AI relies on the competence of teachers, the accessibility of resources, and other social variables. Research into the appropriate integration of AI in mathematics education is further underscored by the post-pandemic educational environment, which has brought new complexities and hastened changes in teaching and learning. In order to tackle this, the research puts out eleven hypotheses that investigate the role of various internal and external aspects in the implementation of AI in elementary mathematics education (Refer to Table 1 and Figure 1).

Table 1 Difinitions of constructs

Construct	Definition
AI Utilisation (AIU)	Refers to the extent to which primary mathematics teachers incorporate AI tools, such as Ernie Bot, a generative AI model for natural language processing that can assist in interactive learning and automated feedback, and Khan Academy's adaptive learning system, which leverages machine learning algorithms to provide personalized learning experiences and real-time feedback, into their teaching practices to enhance learning outcomes.
Technological Content Knowledge and Technological Pedagogical Knowledge (TCK_TPK)	Combines TCK, which is understanding how to use specific technologies to support subject-matter learning, and TPK, which is knowledge of how to use technologies to enhance teaching and learning. Based the TPACK theory, this construct's questions include TCK and TPK aspects, investigating how teachers apply technology specifically in content-related contexts and in broader pedagogical strategies.
TPACK	Unlike TCK_TPK, which focuses specifically on the interplay between technological content knowledge and technological pedagogical knowledge, TPACK represents a comprehensive understanding that inte- grates technology, pedagogy, and content knowledge. It emphasizes how these three domains work together to create effective teaching strategies that are not only content-specific but also grounded in pedagogical and technological expertise.
Attitude	Refers to teachers' perceptions and feelings towards using AI tools in their teaching, influenced by the constructs of PEoU and PU from the TAM. These dimensions are crucial for understanding how teach- ers' attitudes are shaped and their willingness to adopt AI tools.
Educational Challenges (EC)	Includes rigid curriculum standards, school norms, and traditional assessment methods that can influence the adoption of innovative, technology-driven methods.
Contextual Factors (CF)	Encompasses elements such as resource availability, institutional support, and cultural attitudes towards technology, significantly impacting technology integration.
Parental and Community Involvement (PCI)	Refers to the attitudes and support of parents and the wider community towards technology use in schools, playing a significant role in AI implementation.

Hypotheses

H1: Attitude positively influences AIU.
H2: TCK_TPK has a positive effect on AIU. **H3**: TCK_TPK positively influences Attitude. **H4**: TCK_TPK has a positive effect on TPACK.



H5: TPACK positively influences AIU.
H6: TPACK has a positive effect on Attitude.
H7: CF have a positive effect on AIU.
H8: CF positively influence EC. **H9**: EC positively influence AIU. **H10**: PCI positively influences AIU. **H11**: PCI positively influences CF.

Method

Research Design

The complex interrelationships between AIU, TCK_TPK, TPACK, EC, CF, attitude, and PCI are investigated in this work using a quantitative research approach. The Scale of Mathematics Teachers' Technology Integration (SMTTI) was developed specifically for this study in order to do this (Li, 2024). Based on the scales created by Schmidt et al. (2009), Chai et al. (2013), and Li (2023), the SMTTI is a seven-factor, five-point Likert scale (31 questions) questionnaire (see Table 3). This gives a good basis for understanding the complex nature of technology integration in educational settings. The seven components of the survey were adapted from important concepts found in earlier studies and adjusted to fit the unique aspects of artificial intelligence (AI) in elementary mathematics instruction in China. An extensive evaluation of the intricate interplay between AIU and other variables, such as TCK_TPK, TPACK, EC, CF, Attitude, and PCI, is necessary, which is why the SMTTI was conceptualized. Data collected by the SMTTI on these aspects enables a detailed comprehension of the interplay between the many components that impact the uptake and efficacy of AI technologies in elementary mathematics teaching.

The study's quantitative methodology allows for the gathering of data amenable to rigorous statistical analysis, which in turn reveals patterns and possible links (Bryman, 2016). When dealing with complicated models including numerous constructs and indicators, particularly in situations where theory building and prediction rather than theory testing is the objective, Partial Least Squares Structural Equation Modelling (PLS-SEM) was used (Hair et al., 2011). In exploratory studies, PLS-SEM is ideal for maximizing the explained variation of dependent factors and testing the model's predictive capacities. PLS-SEM's adaptability in modeling complicated associations, resilience to non-normal data distributions, and capacity to manage small to medium sample sizes make it an appropriate option for this investigation (Henseler et al., 2015). To fully grasp the elements impacting the use of AI tools in elementary mathematics education, this method allows for an in-depth analysis of the direct, indirect, and total impacts among the constructs.

Using this methodological framework, the research intends to provide empirical evidence to the expanding corpus of knowledge on the elements that impact the use of AI technologies in the field of education, particularly in the context of elementary mathematics instruction.

Participants

This study surveyed primary mathematics teachers in southwest China (Chong- qing) using random sampling, and a total of 498 teachers completed the question- naire. As shown in Table 2, the sample predominantly consisted of female teach- ers (80.3%), which reflects the general trend in China’s primary education sector. Most teachers had more than six years of experience, with a significant portion (44%) having over 15 years of experience. The majority of participants held

Table 2 Demographic information

		Frequency	Percent
Gender	Female	400	80.3
	Male	98	19.7
	Total	498	100
Teaching Experience	0–5	76	15.3
	6–10	119	23.9
	11–15	84	16.9
	Above 15 years	219	44
	Total	498	100
Education Background	Junior college	118	23.7
	Bachelor’s degree	373	74.9
	Master’s degree	7	1.4
	Total	498	100

the sample had a comparatively high level of formal education, with 74.9% holding bachelor's degrees. The elementary school math instructors in this sample are urbanites who focus only on mathematics instruction and who do not teach any other subjects. Typically, these educational institutions boast highly developed systems for information technology.

Thirteen percent in first grade, seventeen percent in second, twenty-one percent in third, sixteen percent in fourth, sixteen percent in fifth, and fifteen percent in sixth grade make up the sample of primary school instructors. The sample as a whole sheds light on the possibilities and threats facing elementary mathematics education in this part of China across all grade levels. To analyze the integration of AI in elementary mathematics education, it is useful to have a general idea of the participant's background, and this demographic data gives just that.

Instrument

To address the research questions, the SMTTI was specifically designed, devel- oped, and validated for this study as detailed in the publication (Li, 2024). The SMTTI was used to investigate the interrelationships among seven key con- structs: Attitude, AIU, CF, TCK_TPK, TPACK, EC, and PCI. Below is Table 3 summarizing the seven constructs, the number of items for each, and examples of corresponding items.

The scale developed for this study exhibits strong reliability and validity, as evidenced by its fit indices, Composite Reliability (CR), and Average Variance Extracted (AVE) values (Li, 2024). These psychometric properties make the SMTTI an effective tool for exploring the complex relationships between these factors in primary mathematics education.

Data Collection

In partnership with Chongqing Jiulongpo District Teacher Education College, this research surveyed elementary school math instructors from around China to compile its findings. The survey was disseminated via WeChat using Qualtrics, guaranteeing quick access and a large reach to participants. Survey distribution relied heavily on the educational institution's network. Ethical compliance was ensured by rigorously maintaining participant confidentiality and anonymity. Demographic information was also requested, and participants were required to sign an informed consent document that described the study's goals and any ethical concerns (Bryman, 2016). The survey also had questions measuring SMTTI. The study lasted a month, and participants were reminded at regular intervals to make sure all the data was collected. The goals and methods of involvement in the research were clearly presented via a digital poster that included a QR code for the survey. Following all applicable ethical guidelines, this strategy achieved a response rate of 49.8 percent (498 replies out of 1000 surveys sent).

Table 3 Item information

Construct	Number	Example Item
TPACK	4	I can effectively integrate digital technology, mathematics knowledge, and teaching methods in online mathematics classes.
TCK_TPK	4	I can use digital technologies to visualize abstract mathematical concepts, for example, by dynamically presenting geometric figures on interactive whiteboards (TCK). I can use digital technologies to design real-time quizzes that assess students' learning effectiveness in class (TPK).
Attitude	5	Using digital technology in my mathematics teaching enables me to effectively achieve instructional objectives.
AIU	5	I believe that AI-driven mathematics tutoring systems can help students improve their learning abilities in mathematics.
CF	5	The national teacher professional development programs help me to master various educational digital technologies.
EC	4	Please rate how strongly you agree or disagree that the following factors motivate your integration of digital technology into mathematics teaching: Standardized tests. (Matrix Table)
PCI	4	My students can use digital communication tools (such as DingTalk, WeChat, and QQ) to collaborate on mathematics tasks.

Data Analysis

In this study, using SmartPLS 4 software to investigate the relationships among the seven factors, PLS-SEM analysis was employed. Additionally, PLS-SEM is particu- larly suitable for research where the primary aim is to explore and confirm poten- tial theoretical relationships, making it ideal for this study's objectives (Hair et al., 2011). The data analysis comprised two main stages: the measurement and struc- tural models.

Measurement Model

Several criteria were used to evaluate the validity of the measurement model. Following the suggested criterion of around

0.70, as proposed by Hair et al. (2018), we examined factor loadings to ascertain the various items' contributions to their respective constructs; the results showed adequate loadings. According to (Dijkstra & Henseler, 2015; Hair et al., 2018), construct reliability was assessed using Cronbach's alpha, CR, and rho_A values. Values over 0.70 were deemed adequate. Because of this, we know the model's constructions are reliable. The AVE values of the constructs were also computed to evaluate the validity of the measurement methodology. More than half of the indicator variation is explained by the latent variable, indicating good convergent validity, when the AVE value is over 0.50, as pointed out by Hair et al. (2018). Additionally, the indicators were tested for multicollinearity using VIF values. In the absence of multicollinearity problems, VIF values close to but below five imply (Hair et al., 2018). In addition, as per the criteria laid forth by Fornell and Larcker (1981), we checked for discriminant validity by comparing the square roots of the AVE values for each construct with the correlations that were shared with other constructs.

Structural Model

The structural model's R2 values for the outcome variables' explanatory power were examined. According to Hair et al. (2018), R2 values of 0.25 imply poor explanatory power, 0.50 moderate explanatory power, and 0.75 strong explanatory power. Using a bootstrapping approach with 5,000 sub-samples and a significance threshold of 0.05, the linkages between structures were explored. To provide a more thorough assessment of the model's explanatory capacity, the research included the examination of f 2 values and the blindfold-ing approach for measuring predictive significance. Q2 values show the predictive strength of the model, with 0.25 indicating medium explanatory power and 0.50 indicating great explanatory power, according to Shmueli et al. (2016). On the other hand, f 2 values—which assess the magnitude of an independent variable's influence on a dependent one—are equally critical in establishing the model's generalizability and significance. The research attempted to comprehensively assess the model's performance in predicting the links across important dimensions by including both Q2 and f 2 measurements. To summarize, the study's results in investigating the relationships among the seven critical factors in AI utilization in primary mathematics education were supported by a thorough evaluation of the measurement and structural models conducted using PLS-SEM. This evaluation ensured the reliability, validity, and predictive power of the study.

Table 4 Measure modal assessment

Construct	Factor loadings	VIF	Cronbach's alpha	rho_a	CR	AVE
AIU	0.899–0.929	3.543–4.808	0.953	0.953	0.963	0.840
Attitude	0.937–0.952	5.308–6.976	0.969	0.969	0.976	0.890
CF	0.901–0.923	3.479–4.386	0.948	0.948	0.960	0.828
EC	0.880–0.910	2.586–3.196	0.914	0.916	0.939	0.795
PCI	0.862–0.898	2.463–3.125	0.905	0.908	0.934	0.779
TCK_TPK	0.869–0.925	2.553–3.982	0.918	0.921	0.942	0.803
TPACK	0.872–0.911	2.641–3.181	0.914	0.918	0.939	0.795

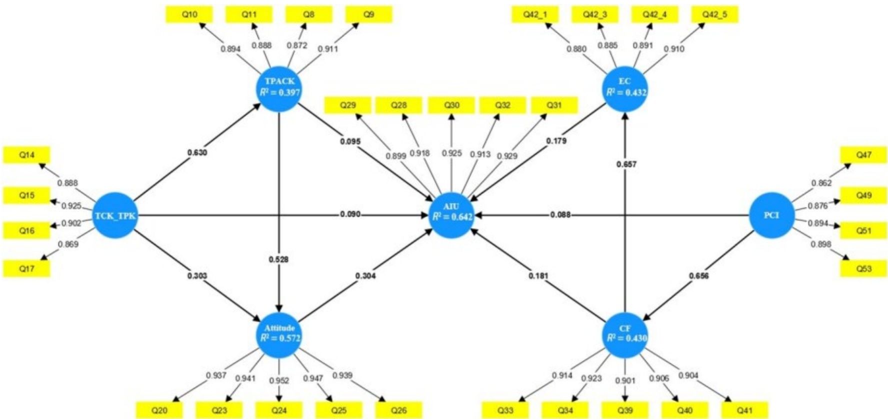


Fig. 2 Path analysis of constructs influencing AIU

Findings

Validity and Reliability Assessment

Table 4 shows that all of the tested constructs in this study's measurement model evaluation have strong psychometric characteristics. Figure 2 shows the factor loadings for the following constructs: AIU, Attitude, CF, EC, PCI, TCK_TPK, and TPACK, which ranged from 0.862 to 0.952. The suitability of the measuring items is confirmed by the high loadings, which indicate large contributions from individual items to their respective constructs. All constructions' VIF values, which ranged from 2.463 to 6.976, fell within acceptable limits in terms of multicollinearity. This provides evidence for the independence of the model's constructs and implies that there are few worries about multicollinearity. With Cronbach's Alpha and rho_a values ranging from 0.905 to 0.969, all constructs demonstrated good reliability in terms of internal consistency, which is defined as reliability scores above the 0.70 threshold. The strong CR scores, which fell within the range of 0.934 to 0.976, further support the robust reliability and guarantee the dependability of the model's structures. Furthermore, with AVE values ranging from 0.779 to 0.89, all constructs demonstrated strong convergent validity, above the proposed limit of 0.50. This suggests that the latent constructs successfully account for a considerable amount of the indicator variation. The results of the discriminant validity test corroborate the findings in Table 5, demonstrating that the model is highly valid. Attitude, AVE square roots, CF, EC, PCI, TCK_TPK, and TPACK all outpaced their relationships with other constructs. Strong discriminant validity is confirmed, guaranteeing that each concept captures its domain uniquely. Thus, all constructs in this research have great reliability and validity, as shown by the measurement model evaluation. Reliability coefficients, factor loadings, VIF values, and AVE values all point to a strong and well-suited model for investigating the interrelationships of the constructs connected to the use of AI technologies in elementary mathematics instruction. The model is well-suited to investigating the complex dynamics of AI integration in educational contexts since the constructs are trustworthy, legitimate, separate, and well specified.

Structural Model Analysis

Influence of External Factors on AIU

Based on Table 6, the study can draw several conclusions about the relationships and predictive capabilities within the studied model. Firstly, the direct effect of attitude on AIU is significant ($\beta = 0.304$, $p < 0.001$) with a small effect size ($f^2 =$ 0.079). While the effect size is relatively small, it still indicates that attitude has a meaningful direct influence on AIU. In contrast, CF exerts both a significant direct ($\beta = 0.181$, $p = 0.002$) and indirect effect on AIU ($\beta = 0.118$, $p <$ 0.001),

Table 5 Discriminant validity

	AIU	Attitude	CF	EC	PCI	TCK_TPK	TPACK
AIU	**0.917**						
Attitude	0.743*	**0.943**					
CF	0.696*	0.735*	**0.910**				
EC	0.669*	0.686*	0.657*	**0.891**			
PCI	0.635*	0.672*	0.656*	0.648*	**0.883**		
TCK_TPK	0.605*	0.636*	0.612*	0.565*	0.579*	**0.896**	
TPACK	0.646*	0.719*	0.655*	0.591*	0.599*	0.630*	**0.891**

The bold number = $\sqrt{AVE}$(e.g., AIU $\sqrt{0.840} \approx 0.917$). * $p < 0.01$

Table 6 Direct, indirect, total effect, and F-square

Hypotheses	Direct effect			Indirect effect			Total effect			f^2
	β	T	***P***	***β***	T	***P***	***β***	T	***P***	
Attitude -> AIU	0.304	5.350	0.000				0.304	5.350	0.000	0.079
CF -> AIU	0.181	3.096	0.002	0.118	3.562	0.000	0.298	5.099	0.000	0.034
CF -> EC	0.657	23.906	0.000				0.657	23.906	0.000	0.761
EC -> AIU	0.179	3.638	0.000				0.179	3.638	0.000	0.039
PCI -> AIU	0.088	1.878	**0.060**	0.196	4.969	0.000	0.283	6.125	0.000	0.009
PCI -> CF	0.656	23.051	0.000				0.656	23.051	0.000	0.754
TCK_TPK -> AIU	0.090	2.056	0.040	0.253	6.540	0.000	0.342	7.154	0.000	0.011
TCK_TPK -> Attitude	0.303	6.952	0.000	0.333	11.434	0.000	0.636	21.278	0.000	0.129
TCK_TPK -> TPACK	0.630	21.644	0.000				0.630	21.644	0.000	0.660
TPACK -> AIU	0.095	1.820	**0.069**	0.160	5.048	0.000	0.255	5.196	0.000	0.010
TPACK -> Attitude	0.528	13.057	0.000				0.528	13.057	0.000	0.393

β means the path coefficients

culminating in a total effect of 0.298 and a small effect size ($f^2 = 0.034$). This suggests that CF influences AIU both directly and through other constructs. CF's impact on EC is marked by a strong direct effect ($\beta = 0.657$, $p < 0.001$) with a large effect size ($f^2 = 0.761$), indicating CF as a potent predictor of EC. Simi- larly, a significant direct effect of EC on AIU ($\beta = 0.179$, $p < 0.001$) is noted, though with a smaller effect size ($f^2 = 0.039$). The direct effect of PCI on AIU is not significant ($\beta = 0.088$, $p = 0.06$), but its indirect effect is substantial ($\beta = 0.196$, $p <$ 0.001), leading to a total effect of 0.283, albeit with a minimal overall impact ($f^2 = 0.009$). A significant direct effect

($\beta = 0.656$, $p < 0.001$) with a large effect size (f^2 = 0.754) indicates that PCI is a strong predictor of CF.

These findings underscore the multifaceted influence of external factors on AIU in primary mathematics education. CF, including resource availability, institutional support, and cultural attitudes towards technology, are crucial in shaping the educational environment and influencing both the direct and indirect utilisation of AI tools. CF significantly enhances EC, highlighting the impor- tance of robust support systems and infrastructures in facilitating technology integration. The non-significant direct effect of PCI on AIU, contrasted with its significant indirect effect, suggests that parental and community involvement primarily operates through other mediating variables, such as CF. This under- scores the importance of a supportive community environment that indirectly influences AI integration by fostering favourable contextual conditions. These results indicate that the broader educational context and community support play a vital role in successfully adopting and utilising AI tools in primary math- ematics education.

Influence of Internal Factors on AIU

The results show that TCK_TPK is a key component that affects several model variables. It is worth mentioning that TCK_TPK has a notable impact on both Attitude and TPACK. The overall effect on Attitude is the most noticeable (β= 0.636, p < 0.001), while the biggest effect size on TPACK is 0.66. Teachers' use of technology in the classroom is significantly impacted by this factor, as seen by the huge effect size of TCK_TPK on TPACK. Meaningful insights may be gleaned from even the smallest model effects (f 2 = 0.129), which indicate minor but important implications on teacher attitudes and technology uptake.
When looking at how TPACK interacts with other concepts, however, a distinct dynamic emerges. The direct impact of TPACK on AIU is not statistically significant (β= 0.095, p = 0.069), even if it has a large influence on attitude (β= 0.528, p < 0.001) and a high effect size (f 2 = 0.393). As a result, the effect magnitude is tiny (f 2 = 0.01). It seems that TPACK plays a significant role in attitude determination, but it has a small effect on AIU. This suggests that there may be mediating variables or indirect pathways at work in the model that need more investigation.
These results show how many internal variables influence AIU in elementary math classes. Teachers' perspectives and general teaching skills are shaped by their technical and pedagogical content knowledge, as shown by the considerable effect of TCK_TPK on both Attitude and TPACK. Teachers' integrated knowledge bases are essential for successful technology integration, and the high influence of TCK_TPK on TPACK further underscores the importance of comprehensive professional development programs that provide just that. A strong knowledge base is necessary for optimal exploitation of AI technologies, but the modest direct influence of TPACK on AIU indicates that this is not enough. Translating TPACK into practical AIU is heavily influenced by other mediating elements, such instructors' attitudes and perhaps external support systems, according to this result. Thus, it is crucial to address TPACK questions effectively in order to encourage positive attitudes towards technology. However, more assistance and resources are needed to connect classroom knowledge with real-world AI applications.

Explanatory and Predictive Power of the Model

Regarding the model's explanatory and predictive power (See Table 7), AIU stands out with a moderate proportion of variance explained (R^2= 0.642) and a large pre- dictive relevance (Q^2= 0.534). This indicates the model's effectiveness in explaining and predicting AIU. For Attitude, CF, EC, and TPACK, the model demonstrates a moderate level of explained variance (moderate R^2 values) and varying levels of pre- dictive relevance. Attitude shows a large predictive relevance (Q^2 = 0.505), suggest- ing the model's strong predictive capability for this construct. CF, EC, and TPACK, with medium predictive relevance (Q^2values of 0.353, 0.34, and 0.312, respectively), indicate a reasonable ability to predict these constructs, albeit not as robustly as AIU or Attitude. Therefore, the model provides insight into the direct, indirect, and total effects among various constructs and their predictive relevance. The findings indi- cate nuanced relationships and varying degrees of influence, which are crucial for understanding the dynamics within the model.

Table 7 R-square and Q-square

	R^2	Consideration	Q^2	Predictive relevance
AIU	0.642	Moderate	0.534	large
Attitude	0.572	Moderate	0.505	large
CF	0.430	Moderate	0.353	medium
EC	0.432	Moderate	0.340	medium
TPACK	0.397	Moderate	0.312	medium

Summary of Hypotheses Testing

Table 8 provides a thorough summary of the study's tested hypotheses. The majority of the hypotheses were confirmed, which means that the model's hypothesized important associations hold. In the context of AI adoption and application, attitude, TCK_TPK, CF, and EC are discovered to significantly and positively impact AIU, highlighting their crucial

functions. The fact that TCK_TPK has a positive effect on attitude and TPACK further demonstrates the model's comprehensive nature.
Two hypotheses were rejected, though: H5, which said that TPACK had no significant direct impact on AIU, and H10, which stated that PCI had no significant direct effect on AIU. The model's complicated dynamics are brought to light by these rejections, which mainly indicate the need for more research into the system's mediated effects and possible indirect paths. According to these results, additional mediating variables may have a pivotal function, as TPACK has a little direct impact on AIU but a substantial influence on attitude. Likewise, contextual variables mediate this link, as PCI has a strong indirect influence on AIU but a non-significant direct impact. These subtleties highlight how difficult it is to include AI into elementary arithmetic lessons.

Table 8 Hypothesis testing results

Hypothesis	Description	Path	Result
H1	Attitude positively influences AIU	Attitude -> AIU	Accepted
H2	TCK_TPK has a positive effect on AIU	TCK_TPK -> AIU	Accepted
H3	TCK_TPK positively influences Attitude	TCK_TPK -> Attitude	Accepted
H4	TCK_TPK has a positive effect on TPACK	TCK_TPK -> TPACK	Accepted
H5	TPACK positively influences AIU	TPACK -> AIU	Rejected
H6	TPACK has a positive effect on Attitude	TPACK -> Attitude	Accepted
H7	Contextual Factors have a positive effect on AIU	CF -> AIU	Accepted
H8	Contextual Factors positively influence Educational Challenges	CF -> EC	Accepted
H9	Educational Challenges positively influence AIU	EC -> AIU	Accepted
H10	Parental and Community Involvement positively influences AIU	PCI -> AIU	Rejected
H11	Parental and Community Involvement positively influences Contextual Factors	PCI -> CF	Accepted

The elementary school system in China may benefit from these results. Both urban and rural schools in China use a wide variety of technology resources, and students face high-stakes exams and demanding curriculum requirements. Reasonable funding, institutional backing, and the integration of AI tools into educational objectives are all imperative in view of the substantial impact of CF and EC on AIU. Community and parental support is essential, but strong institutional frameworks are also necessary to enable successful AI integration, according to the indirect impact of PCI on AIU. This highlights the need of all-encompassing tactics that tackle the educational ecology as a whole (via CF, EC, and PCI) as well as the internal aspects (through TCK_TPK, TPACK, and attitude) of primary mathematics instructors.
This information is vital for stakeholders, educators, and legislators who are trying to increase the use and efficacy of AI in elementary mathematics education because of the fast development of AI and its potential to revolutionize educational methods. This is particularly significant in the post-pandemic age, when the use of digital resources and distance learning has increased, elevating the need of incorporating AI into elementary mathematics curricula.

Discussion

Influence of Internal Factors on AIU in Primary Mathematics Education

This study offers a comprehensive exploration of internal factors influencing the uti- lisation of AI in primary mathematics education, with a specific focus on teacher attitudes, TCK_TPK, and TPACK. The significance of these factors is underscored by integrating theoretical frameworks with empirical findings, providing a nuanced understanding of AI integration within educational contexts.

Teacher Attitudes and AI Adoption

The importance of teacher attitudes in effectively incorporating AI technology into basic mathematics teaching is shown by this research, as shown by H1. In the post-pandemic age, when digital tools have become increasingly integral to education, this critical psychological aspect implies that teachers' intentions to embrace and effectively implement AI tools like Ernie Bot, Qwen, and Khan Academy in their classrooms are greatly influenced by their beliefs and perceptions. The significance of encouraging good attitudes among educators is shown by the substantial impact of teacher attitudes on AIU. Consistent with the TAM's hypotheses (Davis, 1989), this shows that PEoU and PU have a big impact on people's decisions to embrace new technologies. According to Almagren et al. (2024), when teachers have a positive attitude towards AI technology, it shows in their PEoU and PU, which in turn promotes integration. The results also line up with what Ibili et al. (2019) and Teo (2011) have said about the importance of attitudes when integrating technology. Both studies highlighted the significance of encouraging positive attitudes among teachers as a means to successfully integrate new technologies into lesson plans, which is critical for the successful use of artificial intelligence (AI) in elementary mathematics classrooms.

In contrast to other studies, this one zeroes in on a hitherto unexplored area: the employment of AI in elementary mathematics classrooms. For example, whereas Teo (2011) looked at broad technology, Ibili et al. (2019) zeroed down on AR teaching systems. Contrarily, this research explores artificial intelligence (AI) tools for language processing and machine learning, drawing attention to the specific difficulties and potential benefits of introducing these cutting-edge technologies into elementary school mathematics curricula. An under-scoring of the requirement of encouraging favorable views towards AI among teachers highlights the need for focused professional development programs in this area. These kinds of programs are essential for the widespread use of AI technologies because they increase primary school math instructors' openness and competence, which is particularly important in the age after the pandemic, when the use of digital resources has grown exponentially.

Teachers' TPACK and AI Adoption

As shown by Hypotheses 2, 3, and 4, this research shows that TCK_TPK has a considerable influence on Attitude, TPACK, and AIU. This shows that the use of AI technology in elementary mathematics teaching relies heavily on instructors' TPACK. This confirms what other studies have shown: that TPACK is crucial for successful technological integration. To provide only two examples, Mishra et al. (2023) emphasized the need of TPACK in integrating AI technologies with pedagogy and content, while Khong et al. (2023) showed that TCK and TPK had comparable impacts on improving instructors' attitudes and teaching methods. Further establishing the vital significance of comprehensive professional development programs in enabling technology integration, this research expands upon these results by showing the direct and indirect impacts of TCK_TPK on AIU. Despite TCK_TPK's substantial effect on AIU, this research contradicts earlier results by demonstrating that its direct effect on AIU is negligible. This goes against the findings of studies by Mailizar et al. (2021) and Koh et al. (2016), which established causal links between TPACK and the effectiveness of technology integration. This disparity exists because artificial intelligence (AI) technologies present their own set of problems that need more than just a good foundation of knowledge in order to solve.

The increasing reliance on digital resources in the post-pandemic age has highlighted the need for supplementary support systems (Fortus et al., 2023). While TPACK is crucial for encouraging favorable attitudes towards AI, this research implies that other elements, such instructors' attitudes and external assistance, may play important roles in turning TPACK into effective AIU. In order to close the gap between theory and practice, the results suggest that all-encompassing professional development programs should fix these extra issues in addition to improving TPACK. This research emphasizes the need for comprehensive assistance for successful integration of AI in education, which is one of its main justifications. The fact that there was no statistically significant relationship between TPACK and AIU lends credence to this claim (H5). This raises the possibility of indirect channels and the need for more research into mediated effects, suggesting the existence of complicated dynamics within the model.

Influence of External Factors on AIU in Primary Mathematics Education

The results of this research (H7 and H9) show that CF and EC have a substantial effect on AIU. This discovery further supports the idea that technology adoption is complex and involves many factors. For example, prior research has looked at the importance of education resources, institutional support, curriculum alignment, school norms, and traditional assessment methods in integrating digital technology into primary mathematics education (Hew & Brush, 2007; Vongkulluksn et al., 2018; Koh, 2018; Erdmer et al., 2012). For example, Tondeur et al. (2017) found that schools that had strong technical resources and support from administrators were better able to integrate digital technology into their lessons. On the other side, schools that lack enough funding or administrative support often face challenges when trying to use these technology.

But by including PCI, this research brings a fresh perspective. There was no statistically significant relationship between PCI and AIU (H10) in this investigation. On the other hand, PCI did impact AIU indirectly, which suggests a more nuanced interaction between the two processes. The direct influence that is often assumed in the literature (del Olmo-Muñoz et al., 2023; Lawrence & Fakuade, 2021) is challenged by this discovery. The importance of fostering stronger community relationships and actively engaging parents and community members in schools' efforts to integrate AI cannot be overstated. The transition from passively receiving information to actively participating creates an atmosphere that is favorable to the successful integration of AI in elementary mathematics classes. In order to successfully integrate AI into elementary mathematics education, it is imperative that we address CF and EC while simultaneously including the larger community.

Implications

For the purpose of incorporating AI technologies into elementary mathematics curricula, this study's results provide four recommendations. First, it is crucial to encourage favorable views regarding AI among teachers, as these sentiments have a substantial impact on AIU. This may be accomplished by implementing focused professional development programs that aim to improve teachers' technology proficiency knowledge (TPACK) and tackle the psychological obstacles that prevent them from embracing technology. For example, it would be beneficial to provide training programs and seminars that show instructors how to utilize AI tools like Khan Academy, Qwen, and Ernie Bot, and give them the confidence to use these tools effectively in the classroom. These projects aim to improve instructors' proficiency in using AI technologies, which may lead to a more open attitude towards AI inclusion.

Secondly, the need for all-encompassing support systems is underscored by the fact that TPACK has a negligible direct influence on AIU, but substantial indirect impacts via attitudes and other mediating variables. To ensure that instructors are able to put their TPACK into practice in the classroom, educational institutions should provide continuous technical and pedagogical assistance. Included in this might be chances for teachers to collaborate with their peers, access to AI specialists, and ongoing professional development to stay abreast of AI developments and how to effectively incorporate them into the classroom.

Third, policy shifts, resource distribution, and institutional backing are essential for successful AI integration, since CF and EC play substantial roles in AIU. To facilitate the deployment of AI technologies, schools need strong technical infrastructure as well as administrative assistance. To make sure that everyone can use AI, lawmakers should put money into digital infrastructure, especially in underprivileged regions. To further alleviate the difficulties caused by conventional pedagogical methods and inflexible curricular frameworks, it is recommended to integrate AI in accordance with established standards and assessment procedures.

Lastly, it is important to include parents and community people in AI integration initiatives, since PCI indirectly influences AIU. Having parents participate in AI-related talks and events is a great way for schools to strengthen community relationships. Workshops, instructive seminars, and collaborative projects showcasing AI's worth in improving learning outcomes might accomplish this. Schools may improve the efficacy of AI integration in elementary mathematics instruction by fostering a supportive community climate.

Limitations and Future Study

The study's limitations include its exclusive focus on elementary math educators in one part of China and its lack of applicability to other regions or grade levels. Because it only records data at one moment in time, the cross-sectional design makes it difficult to draw conclusions about cause and effect or track how AI integration has evolved over time. There is a risk of biases like social desirability bias when data is based on self-reports. Taken together, these issues weaken the study's credibility and reliability of its findings.

To circumvent these restrictions and increase the findings' generalizability, future studies should recruit participants from a wider range of geographic locations and educational backgrounds. To better understand how AI is being used in the classroom and how instructors' perspectives and methods are evolving over time, longitudinal research would be a great asset. Validating the results and reducing the biases in self-reported data might be achieved by using objective measurements or observational data. To further establish the results' general applicability and improve their external validity, future research should think about doing similar investigations in other cultural and educational settings. To get a better grasp of how educators have interacted with AI and to gain more nuanced insights particular to their setting, qualitative approaches like focus groups or interviews might be useful. Curriculum alignment, the influence of AI on student outcomes, and the impact of certain AI technologies might all be the subject of future study. A more complex picture of AI integration in education might be revealed by studying possible mediating and moderating variables, such institutional support and community participation. By delving into these topics, future research on artificial intelligence (AI) in education may expand our understanding of the topic and inform both policy and practice.

Conclusion

The internal and external aspects that impact the deployment of AI in elementary mathematics education in China are thoroughly examined in this research. The results emphasize the importance of focused professional development and the favorable influence of teachers' attitudes toward artificial intelligence (AI), as well as their TCK_TPK and TPACK. To put knowledge into practice, particularly in the aftermath of a pandemic, TPACK is necessary, but it is not sufficient on its own. Changes in policy, the distribution of resources, and the backing of institutions are all required by external variables like CF and EC. Parents and communities should be actively involved in efforts to integrate AI and create a supportive atmosphere since PCI may indirectly affect CF. To effectively incorporate AI into elementary mathematics education, which would be beneficial for kids and teachers alike, professional development, increased support, and strong community involvement are all necessary considerations.

Finally, by illuminating the interaction of several elements that impact its acceptance, this research offers important insights into the complexity of AI integration in education. Contributing to the continuous development of AI-enhanced learning environments, the results provide the groundwork for future research and practical initiatives to improve the successful use of AI technology in educational settings.

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