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Teachers' Adoption of AI tools in Education through the Lens of Technology Acceptance Model and Task-Technology Fit

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Teachers' Adoption of AI Tools in Education through the Lens of Technology Acceptance Model (TAM) and Task-Technology Fit (TTF)

1. Introduction

The rapid advancement of Artificial Intelligence (AI) in education has the potential to not only automate repetitive tasks but also fundamentally transform pedagogy and assessment [1], [2]. While prior studies have largely focused on the impact of AI on student outcomes, such as learning gains and engagement, whether these technologies achieve meaningful classroom integration depends heavily on one crucial actor: the teacher [3], [4]. As primary agents of instructional change, teachers' willingness to adopt, adapt, and embed AI tools into their daily teaching directly shapes the effectiveness and sustainability of technology use [5], [6].

However, current literature reveals a strong student-centered bias. Despite the increasing availability of generative AI (GenAI) tools like ChatGPT and Copilot, large-scale empirical studies on how teachers actually perceive and use these tools remain limited. Most research remains based on small samples, qualitative case studies, or early conceptual work, leaving a gap in our understanding of the behavioral and psychological mechanisms underlying teachers' adoption of GenAI tools [7], [8]. Moreover, while classic frameworks such as the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF) have been widely discussed, there is limited descriptive evidence on how the specific dimensions of these frameworks (Perceived Usefulness, Perceived Ease of Use, Behavioral Intention/Attitude toward Use, and Task-Technology Fit) manifest in real classroom contexts [9], [10], [11]. Furthermore, given the distinct pedagogical demands of engineering and science education, such as complex problem-solving and technical demonstrations, it remains under-explored whether disciplinary background (i.e., STEM vs. non-STEM) significantly shapes teachers' acceptance and perceived fit of AI tools.

This study aims to address these gaps by utilizing the core constructs of TAM and TTF as a descriptive lens to explore Chinese teachers' usage patterns, attitudes, and support needs related to AI tools in education. Specifically, we investigate the following research questions (RQ):

RQ1: What are the current usage patterns of AI tools among teachers in education (e.g., frequency, types of tools, and pedagogical adjustments)?

RQ2: What attitudes do teachers hold toward the integration of AI tools in their teaching practices?

RQ3: What challenges and support needs do teachers identify for the effective use of AI in education?

RQ4: To what extent do STEM and non-STEM teachers differ in their acceptance of AI tools, specifically concerning Perceived Usefulness, Perceived Ease of Use, Attitude, and Task-Technology Fit?

Theoretically, this research draws upon the foundational dimensions of TAM and TTF to structure a comprehensive descriptive profile of teachers' AI adoption, integrating contextual variables such as ethical concerns and operational barriers. Practically, the findings provide actionable insights for teacher training and institutional planning, helping to tailor AI integration strategies to specific disciplinary needs, particularly in engineering and STEM education.

To address these questions, a large-scale teacher survey grounded in TAM and TTF frameworks has been conducted. Descriptive analyses were used to examine usage patterns, attitudes, challenges, and perceived needs, providing an integrated view of AI adoption in teaching.

2. Literature Review

2.1. Theoretical Foundation

The Technology Acceptance Model (TAM) was developed by Davis (1985) [12] and is grounded in the Theory of Reasoned Action proposed by Fishbein & Ajzen (1975) [13]. This framework serves as a base for identifying the determinants of human behavior related to the acceptance or rejection of technological systems. Two perceptual constructs serve as foundational determinants of TAM: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU denotes the degree to which an individual believes that a technology will improve their work or learning performance, while PEOU reflects the belief that interacting with the system will require minimal effort. These constructs jointly inform the user's attitude toward the technology, which in turn shapes behavioral intention (BI) and ultimately actual usage behavior. While TAM traditionally posits these as causal pathways, the present study adopts PU, PEOU, and BI purely as descriptive dimensions to evaluate teachers' current baseline attitudes. Another model, the Task-Technology Fit (TTF), proposed by Goodhue & Thompson (1995) [14], argues that for a technology to have a positive impact on individual performance, it must be utilized and its functionalities must be a good match for the requirements of the task being performed [15]. The core concepts of this model are: i) task characteristics, ii) technology characteristics, iii) utilization, and iv) performance impacts.TTF shifted the research focus from intent to use, as in TAM, to the utility and post-adoption benefits of technology. TTF is often examined alongside TAM to provide a more holistic view of adoption and utility [16], [17], [18]. Therefore, using constructs from both frameworks allows researchers to systematically describe the perceived acceptance of AI tools and their functional compatibility with specific teaching tasks, particularly in rigorous disciplines such as STEM and engineering education. For instance, the teaching tasks in STEM and engineering education often involve coding, spatial reasoning, and laboratory data analysis, which demand highly specific AI functionalities (e.g., algorithmic problem-solving). In contrast, non-STEM disciplines may prioritize text generation or qualitative critique. Consequently, the Task-Technology Fit, as well as perceived usefulness, may inherently differ across these disciplinary boundaries.

2.2. Current Application of AI in Education

Although there has been an increase in research on teachers' AI adoption in recent years (from 2019 to 2024), and TAM being the most commonly used theoretical framework, there is still a lack of deeper exploration of factors unique to the educational context, such as transmissive and constructivist pedagogical beliefs [19], [20], professional insecurity or AI anxiety [21], personal innovativeness [22], alignment with disciplinary pedagogy, academic integrity concerns [21], and the need to accommodate diverse student cognitive levels [23], [24]. In the meta-analysis conducted by Taheri et al. (2025) [25], some factors that influence educators' AI adoption were identified. However, among the 45 articles analyzed by Taheri et al. (2025) [25], no article used combined frameworks: TAM and TTF [25]. Therefore, studies on how both TAM and TTF frameworks could be used together to explore the teachers' AI adoption, specifically, whether AI actually supports teaching tasks, are lacking in the literature.

ElSayary's (2024) [26] research focused on teachers' perceptions of ChatGPT. Although it was found that teachers benefit from ChatGPT use in terms of lesson planning, teaching, and learning, the key takeaways were from the students' viewpoint, such as the increased engagement and motivation. Espartinez (2024) [27] also examined perceptions of ChatGPT, not only among teachers, but also among students. Diverse perceptions were found about distinct factors reflecting ethical, innovative, and useful viewpoints [27].

Wang et al. (2024) [28] performed a bibliometric analysis of 2,223 research articles and a content analysis of 125 papers focused on artificial intelligence in education (AIED). The authors found that 40% of the articles concentrated on adaptive learning and personalized tutoring applications, indicating a student-centered emphasis in this field [28]. Similarly, an analysis of the literature review by Mustafa et al. (2024) [29] revealed that most of the studies (53.51%) revolve around students, with teacher-focused studies being the second-highest (39.45%). The dominant learner-oriented framing in these meta-research indicates a disproportionate focus on student outcomes and experiences.

2.3. Teachers' Attitudes towards AI and Challenges

Peñafiel-Jurado's (2024) [30] systematic review of AIED focused on teachers' perspectives. This study reveals that there is an increasing interest in AI tools that can optimize the management of administrative tasks, provide support in the learning of complex content, and facilitate personalized learning. The study also points out some challenges, such as a lack of teacher training and ethical concerns about privacy, and a need to develop educational policies to facilitate access to AIED [30].

Further, some other opportunities for AI adoption by educators were identified, such as classroom management (personalized learning and operational efficiency) [25], [31], [32], and professional growth. However, literature has also reported several challenges and resistance to using AI systems [33], [34], [35] related to insufficient professional development and training [25], [31], academic integrity and ethics concerns [25], [32], [33], overreliance on AI, and job displacement. Additionally, it was found that teachers' lack of motivation[36], infrastructural inequities [32], difficulties in collaborating with others, bureaucratic issues, and limited funds [31] adversely impact AI adoption and utilization.

3. Method

This research adopts a quantitative, survey-based research design to explore Chinese in-service teachers' adoption of AI tools in education. It employs a structured questionnaire, distributed online, to collect large-scale empirical data; see Figure 1. This data is then validated, followed by quantitative analysis of the validated data in three stages: descriptive statistics for baseline usage; subscale reliability testing; and inferential comparative analysis (independent-samples t-tests) to examine disciplinary differences, as well as frequency analysis of perceived challenges and support needs.

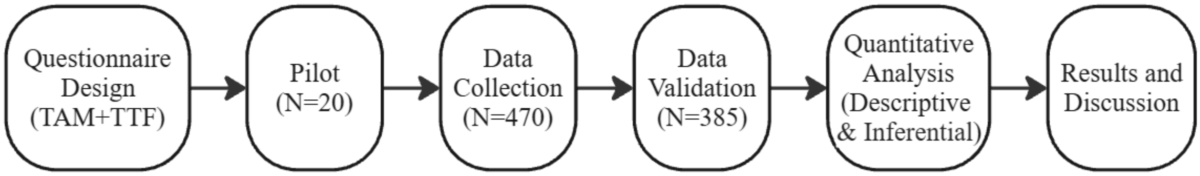

Figure 1.Flowchart depicting the steps of the overall Research Method

3.1. Participants and Data Collection Procedure

The data collection process was conducted via an anonymous online survey distributed through Wenjuanxing, a commonly used digital platform for academic research in China. Given the exploratory nature of this study, a convenience sampling method was employed primarily for its accessibility and efficiency in participant recruitment [37]. This approach allowed researchers to capture initial exploratory data across a diverse range of disciplines, including STEM, Humanities, and Social Sciences. The survey was open during August 2025, and participants were invited through professional networks, school communication channels, and social media platforms. All responses were collected anonymously and voluntarily.

Before the full-scale distribution, the survey questionnaire was piloted with a small group of 20 teachers to ensure clarity, content validity, and language appropriateness. Feedback from the pilot phase was used to revise several items for improved comprehension and alignment with the teaching context. The survey yielded a total of 470 initial responses from individuals across different educational levels and subject areas in China. The 470 initial responses were screened considering the use of AI tools in teaching practice. 385 out of the 470 initial responses reported using AI tools in their teaching practice, and this constitutes the final valid sample (N = 385) for the core quantitative analysis of this study.

3.2. Measurement instrument

The survey instrument used in this study is a self-developed questionnaire theoretically grounded in the Technology Acceptance Model (TAM) and the Task-Technology Fit (TTF) framework. Informed by prior validated measures [38], [39], the questionnaire incorporates four core constructs relevant to teachers' cognitive, affective, and behavioral responses toward AI tools in education: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention/Attitude toward Use (ATT), and Task-Technology Fit (TTF). Each of these constructs is measured using three items, resulting in a total of twelve Likert-scale questions rated on a five-point scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). In line with best practices for survey design, a reverse-coded item concerning interface complexity is included within the PEOU construct to reduce acquiescence bias.

Beyond the theoretical constructs, the questionnaire included additional sections assessing teachers' actual use of AI tools in educational practice. Demographic information, such as specific area taught, was also collected to categorize participants into STEM and non-STEM groups for subsequent comparative analysis. Furthermore, two additional items are included to examine external factors influencing AI adoption, specifically perceived challenges encountered when using AI tools and teachers' support needs for effective AI integration. Together, these components provided a comprehensive assessment of teachers' perceptions, behaviors, and contextual factors related to AI adoption in education. A list of construct categories and corresponding variables used in the questionnaire is provided below in Table 1.

Table 1. Survey Constructs, Variables, and Number of Items

Construct Category	Variables	Cronbach's Alpha	No. of Questions
TAM	Perceived Usefulness (PU): Efficiency in lesson planning, Support for personalized learning, and Reduction of repetitive tasks	0.448	3
	Perceived Ease of Use (PEOU): Perceived ease of use, Clarity of feedback, and Interface complexity	0.518	3
	Behavioral Intention (ATT): Enjoyment, Future use, and Peer recommendation	0.539	3
TTF	Match with teaching needs, Relevance to core tasks, and Perceived effectiveness	0.548	3
Usage in Educational Practice	Actual use of AI tools, Frequency of usage, Type of tools used, Instructional changes, Student involvement, and Differentiated guidance	Not Applicable (NA)	6
Demographic Background	Gender, Teaching Level, Teaching Experience, and Disciplinary Background	NA	4
External Factors & Support	Perceived Challenges and Support Needs	NA	2

3.3 Data Analysis

Quantitative analysis of the collected data is performed using the IBM SPSS Statistics package (Version 26). The analysis proceeds in three phases. First, descriptive statistics are used to analyze teachers' frequency of use, preferred tool types, and common usage scenarios, providing a foundational overview of current integration patterns (addressing RQ1). Second, the reliability of the measurement scales is assessed using Cronbach's Alpha coefficient to ensure internal consistency. Then, descriptive statistical analyses are conducted to evaluate the central tendencies and dispersion of teachers' attitudes, which include mean and standard deviation measurements. These analyses provide the empirical basis for answering the research questions regarding the current state of AI adoption in education (addressing RQ2). After that, descriptive analysis is again used to summarize the types of challenges and support needs most commonly chosen by teachers (addressing RQ3). Finally, to further explore whether disciplinary background influences teachers' attitudes toward AI tools, an independent-samples t-test was conducted comparing STEM teachers and non-STEM teachers (Addressing RQ4). As these items are part of a multiple-response question, results are interpreted based on the number and percentage of total respondents (N = 385) who chose a specific option.

4. Results

4.1. Teachers' AI Tool Usage in Educational Practice

4.1.1. Frequency of AI Tool Usage

The data reveals that a significant majority of teachers have already integrated AI tools into their teaching practices. Specifically, 81.9% of the respondents reported having used AI tools in education, while the remainder indicated they did not. This suggests that the use of AI in classrooms has become a mainstream practice rather than a niche activity. Regarding how often teachers use these tools, the results show that most of them spend a moderate amount of time on AI tools each week. About 57.4% of teachers reported using AI for 3 to 5 hours per week, while 35.8% used it for 1 to 3 hours. A small portion, 4.7%, used AI tools for less than 1 hour weekly, and only 2% reported more than 5 hours of use. These findings indicate that while AI tool adoption is widespread, the weekly time commitment for the vast majority of teachers remains heavily concentrated in the 1 to 5-hour range, suggesting it currently serves as a supplementary practice rather than consuming a dominant portion of their weekly workload.

4.1.2. Types of AI Tools Used

Teachers use a variety of AI tools to support different aspects of their teaching. The most frequently used category is embedded AI platforms and academic management tools (49.36% of N = 385), such as SmartTree and Rain Classroom. These tools help teachers manage courses and track student progress. The second most popular type is instructional design and teaching assistance tools (44.04%), like automatic presentation generators or AI tools in WPS Office. These support the planning and delivery of lessons. Tools that support STEM and programming (36.17%) and intelligent assessment and grading (37.02%) are also widely used, reflecting their importance in technical and evaluation tasks. Less frequently used are content generation tools (25.32%) and multimodal AI tools such as those for voiceover or automatic subtitling (25.32%). Interactive AI tutors or teaching assistants are the least used (3.62%), which may be due to their limited availability or the need for more specialized training to use them effectively. While these descriptive statistics provide a macro-level overview of preferred tools, specific utilization patterns and perceived alignment with teaching tasks may diverge significantly based on disciplinary backgrounds, which will be further explored through comparative analyses in subsequent sections.

4.1.3. Pedagogical Impact and Teaching Adjustments

The integration of AI tools appears to have influenced teachers' instructional methods. A large proportion of teachers (98.7%) reported that AI tools led them to make changes to their instructional design. This suggests that AI is not just used as a tool for convenience but is shaping how lessons are planned and delivered. Moreover, 99.2% of teachers said they either recommend or allow students to use AI tools. While this combined metric indicates a general baseline of openness toward technological engagement, it is important to acknowledge that passively allowing AI use and actively recommending AI as a structured pedagogical practice represent distinct levels of integration. In addition, 98.4% of teachers reported that they tailor their AI guidance based on students' grade level or ability. This highlights that teachers are thinking critically about how to apply AI in ways that are developmentally appropriate.

4.2. Teachers' Attitudes and Behavioral Intentions Towards AI Tool

4.2.1. Reliability and Validity Assessment

The internal consistency of the survey instrument was evaluated using Cronbach's alpha. The overall instrument demonstrated a high level of reliability ($\alpha = 0.862$ for the 12 items), indicating strong internal consistency for the general construct of AI acceptance. However, when evaluating the subscales individually, the Cronbach's alpha values were lower: PU ($\alpha = 0.448$), PEOU ($\alpha = 0.518$), ATT ($\alpha = 0.539$), and TTF ($\alpha = 0.548$).

While these subscale values fall below the traditional 0.70 threshold, this is a common statistical artifact in scales with a very small number of items [40], [41], only 3 items per construct in this study. Cronbach's alpha is highly sensitive to the number of items, and short scales frequently yield lower alpha estimates despite having acceptable inter-item correlations. Additionally, the rapid evolution of generative AI means that teachers' perceptions are highly heterogeneous and context-dependent, which can introduce variance into specific sub-constructs. Therefore, while the overall instrument robustly measures general AI acceptance, the subscale findings should be interpreted as descriptive indicators rather than strict psychometric measurements.

4.2.2. Overall Attitudes Toward AI Integration

The results indicate a predominantly positive attitude among the surveyed teachers. As shown in Table 2, the mean scores for the four dimensions, PU, PEOU, TTF, and ATT, all clustered around 3.90 on a 5-point scale. These mean scores, situated above the neutral midpoint (3.0), suggest that AI acceptance in education is gaining traction across the sample. The relatively low standard deviations (ranging from 0.64 to 0.66) further indicate a general level of descriptive agreement among participants regarding their positive reception of AI tools.

4.2.3. Analysis of Perceived Usefulness and Task-Technology Fit

Among the four constructs, Perceived Usefulness (Mean Rating = 3.91, SD = 0.64) and Task-Technology Fit (Mean Rating = 3.91, SD = 0.65) achieved the highest mean scores. This descriptive finding highlights the pragmatic nature of teachers' adoption of technology. The data suggest that teachers explicitly recognize the functional value of AI in solving specific educational problems. The high rating for Task-Technology Fit indicates that current generative AI tools are perceived to align well with core demands of the teaching profession, such as content generation and assessment efficiency. Consequently, there appears to be a strong descriptive alignment between the perceived "fit" of the technology's capabilities and the positive attitudes observed in this study.

4.2.4. Evaluation of Ease of Use and Behavioral Intention

The score for Perceived Ease of Use (Mean Rating = 3.86, SD = 0.65) was consistent with the other dimensions. While it includes a reverse-coded item regarding interface confusion, the high overall mean suggests that technical barriers are not severely deterring usage for the majority of the sample.

Furthermore, these positive perceptions translated into high self-reported Behavioral Intention (Mean Rating = 3.90, SD = 0.66). This construct reflects the participants' reported willingness to continue using AI and to recommend it to colleagues. The descriptive consistency between perceived usefulness, task fit, and the intention to use aligns with the general theoretical assumptions of the TAM framework. The data suggest that, from a descriptive standpoint, teachers are active proponents who intend to integrate AI more deeply into their pedagogical practices.

Table 2.Descriptive Statistics for Constructs that influence Teachers' Attitude toward AI Tools (Rating range: 0 - 5)

Construct	**Min Rating**	**Max Rating**	**Mean Rating**	**Std. Dev. (SD)**
Perceived Usefulness (PU)	1.33	4.67	3.91	0.64
Perceived Ease of Use (PEOU)	1.33	4.67	3.86	0.65
Task-Technology Fit (TTF)	1.33	4.67	3.91	0.65
Attitude/Behavioral Intention (ATT)	1.33	5.00	3.90	0.66

4.3. Teachers' Challenges and Support Needs Towards AI Tool Adoption and Use

4.3.1. Challenges Teachers Face in Using AI Tools

To understand the main difficulties teachers face when using AI in their teaching practice, the responses by 385 teachers to a multiple-choice question listing possible difficulties are analyzed. The results show that the most reported challenge is a lack of operational proficiency, selected by 234 teachers (60.78%). This suggests that many teachers still feel unfamiliar with AI tools and may require additional training to use them confidently. Another major concern reported is the uncertainty of AI-generated outcomes, reported by 193 teachers (50.13%). This reflects teachers' hesitation in relying on AI tools due to inconsistent or unpredictable results. Furthermore, 208 teachers (54.03%) expressed concerns related to academic integrity, indicating worries that AI tools may encourage plagiarism or inappropriate student use. Ethical and policy-related issues were also raised, with 178 teachers (46.23%) highlighting unclear policies or ethical guidelines as a barrier. Some respondents also pointed out that AI tools do not always align well with their teaching tasks, with 80 teachers (20.78%) reporting issues related to poor task-tool alignment. A small number of teachers (6 teachers, 1.56%) mentioned limited mechanisms for guiding students' use of AI, showing that only a few perceive this as a major challenge.

4.3.2. Teachers' Support Needs for Effective AI Integration

Teachers were also asked what types of support they would like to receive to better integrate AI into their teaching. Among the 385 respondents, the most frequently selected option was the need for clear policies and ethical guidelines, chosen by 277 teachers (71.95%). This highlights a strong desire for institutional direction on responsible and appropriate AI use. In addition, 248 teachers (64.42%) expressed interest in access to a teaching case repository, suggesting that practical examples and real teaching cases could help them understand effective ways to apply AI tools. The need for an AI tool usage manual was also reported by

180 teachers (46.75%), indicating that teachers value straightforward, step-by-step guidance. Some teachers also requested a standardized framework for AI use in classrooms, selected by 155 teachers (40.26%). Meanwhile, 101 teachers (26.23%) expressed interest in hands-on workshops, showing that although workshops are helpful, they are not the most preferred form of support.

A strong connection can be seen between the challenges teachers reported and the types of support they hope to receive. The widespread concern about unclear policies and ethical issues is reflected in the high demand for formal policy and ethical guidelines, suggesting that teachers are looking for clearer institutional direction to help them use AI responsibly. Likewise, the challenge of limited operational proficiency is closely linked to teachers' requests for AI tool manuals and teaching case libraries, which can offer practical, easy-to-follow examples to guide classroom use. In addition, the concern about unstable output quality highlights why many teachers also prefer standardized frameworks and real-world cases that can help them judge when and how AI tools can be used effectively. Overall, the support teachers seek directly responds to the difficulties they face, showing a clear alignment between their needs and the barriers identified.

4.4. Differences in AI Acceptance Between STEM and Non-STEM Teachers

The results revealed a broad consensus across disciplines regarding the overall utility and behavioral intentions toward AI. For all items measuring PU, ATT, and the majority of PEOU and TTF items, no statistically significant differences were found between the two groups (all $p > .05$). This indicates that teachers recognize the functional value of AI equally, regardless of their disciplinary background.

However, when examining responses at the item level to capture detailed disciplinary differences, significant differences emerged in two specific areas: perceived ease of use and match with teaching needs. Non-STEM teachers reported significantly higher scores on perceived ease of use ("I can easily master AI tool operations"; $M = 3.92$, $SD = 0.898$) compared to STEM teachers ($M = 3.65$, $SD = 0.982$); $t(383) = -2.576$, $p = .010$, Cohen's $d = 0.293$.

Furthermore, non-STEM teachers scored significantly higher on match with teaching needs ("My teaching requires rapid generation of diverse materials"; $M = 3.91$, $SD = 0.875$) than their STEM counterparts ($M = 3.65$, $SD = 0.902$); $t(383) = -2.585$, $p = .010$, Cohen's $d = 0.294$. Although the effect sizes are relatively small, these targeted differences provide valuable insights into how distinct academic disciplines interact with generative AI. Specifically, current widely used AI models are predominantly Large Language Models (LLMs) that excel at text generation, which naturally aligns with the rapid demands for material creation in non-STEM fields (e.g., humanities, languages). In contrast, STEM and engineering curricula often require strict mathematical accuracy, complex spatial reasoning, or specialized coding, areas where current AI tools still exhibit friction, thereby slightly lowering the perceived ease of use and task match for engineering teachers.

5. Discussion

5.1. General Overview: From Niche Novelty to Mainstream Utility

The results of this study indicate that AI is no longer an edge technology but has become a mainstream component in China's education sector. 81.9% of the participants reported actively using AI tools, with the majority spending 3 to 5 hours per week on them. These figures suggest that the adoption of AI has transitioned from the "early adopter" stage to a period of stability and integration. Such a high adoption rate aligns with the core descriptive dimensions of the TAM in this context: teachers use these tools not merely because they are novel, but because they consider them crucial to their professional workflow. The strong willingness (98.7%) to adjust teaching designs further indicates that AI holds the potential to act as a catalyst for teaching transformation, shifting the focus from traditional teaching methods to more technology-enhanced strategies.

5.2. The "Pragmatic Adopter": Interpreting TAM and TTF Results

A key insight from the quantitative analysis is the consistency between perceived usefulness (PU) and task-technology fit (TTF), both scoring highest among all constructs (Mean Rating = 3.91; see Table 2). This indicates that the teachers in the sample are "pragmatic adopters" - their positive attitudes (see ATT Mean Rating = 3.90 in Table 2) are closely associated with how well AI tools support specific tasks like planning and assessment, rather than by general enthusiasm for the technology.

The descriptive findings resonate with the foundational premise of TTF: technology adoption is highly correlated with its alignment to specific task requirements. The preference for "embedded AI platforms" and "teaching design tools" over general chatbots further indicates that teachers tend to choose tools that can seamlessly integrate into their existing work environment to solve specific problems, rather than standalone tools that would disrupt their workflow. Furthermore, while the Perceived Ease of Use score (Mean = 3.86; see Table 2) remained highly positive and consistent with other dimensions, responses to reverse-coded items indicated specific instances of technological friction (e.g., interface complexity). This suggests that while pragmatic usefulness strongly corresponds with AI adoption, addressing specific operational barriers remains an important area for technical optimization.

5.3. The Paradox of Openness and Anxiety

One of the most subtle findings in this study is the contradiction between teachers' open attitude towards students' use of AI and their concerns about academic integrity. Despite 99.2% of teachers allowing or recommending students to use AI, a significant portion (54.03%) still consider academic integrity a major challenge. This indicates that teachers adopt a "positive management" approach rather than a "prohibiting" one. Although they are concerned about plagiarism and recognize the futility of banning AI, they choose to guide its use (tailored guidance for different grades, 98.4%). This reflects their deep understanding of the modern classroom, where AI is seen as both a powerful ally for personalized learning (a key component of PU) and a potential threat to traditional assessment methods. This contradiction explains the high demand for clear ethical guidelines (71.95%) noted in the support needs analysis; teachers are willing to innovate but desire a regulatory safety net to mitigate risks. However, as noted in the results, it is crucial for future studies to disaggregate passive tolerance from active pedagogical integration to fully unpack this apparent openness.

5.4. Bridging the Gap: The Mismatch Between Proficiency and Training

A key issue revealed in this study is the mismatch between the challenges teachers face and the kinds of support they prefer. Although many teachers say they lack operational skills (60.78%), hands-on workshops were the least preferred support option (26.23%). Instead, teachers prefer practical resources such as case repositories (64.42%) and usage manuals (46.75%). This finding suggests that teachers want flexible, immediately useful materials rather than general training sessions. They want to see real examples of how AI can be used in their subject areas, and they want reference tools they can use while working. The strong demand for ethical and policy guidelines further suggests that teachers need clarity not only on how to use AI, but on what rules and expectations should guide its use.

5.5. Disciplinary Nuances: Material Demands and Natural Language Interfaces

The comparative analysis between STEM and non-STEM teachers reveals a fascinating dynamic regarding how specific disciplines interact with generative AI. The data indicate that non-STEM teachers have a significantly higher task demand for rapidly generating diverse instructional materials (match with teaching needs). This aligns logically with the nature of humanities, arts, and social science disciplines, which often rely on extensive textual analysis, varied case studies, and diverse media, making the generative capabilities of AI particularly relevant to their pedagogical needs.

Additionally, non-STEM teachers reported greater ease in mastering AI tools (perceived ease of use). Since current GenAI platforms are predominantly driven by natural language prompting rather than formal programming or complex software navigation, teachers with strong linguistic and communication backgrounds may experience a smoother learning curve. This finding challenges the traditional assumption that STEM teachers hold a universal advantage in technology adoption, suggesting instead that the natural-language interface of modern AI creates a highly inclusive environment that particularly benefits non-STEM users. For the engineering and STEM education community, these findings highlight a critical frontier: to achieve the same level of seamless adoption seen in the humanities, future AI development must evolve beyond natural language generation to better accommodate the rigorous computational, spatial, and analytical demands inherent to engineering pedagogy.

6. Conclusion

This study offers a detailed descriptive overview of how in-service teachers in China are adopting AI tools in their everyday teaching, utilizing core dimensions from the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF) as an analytical lens. The results indicate that AI has rapidly transitioned from a niche novelty to a mainstream instructional practice, with teachers leveraging these tools to improve efficiency and support personalized learning. Overall, teachers hold positive attitudes toward AI, with baseline perceptions of usefulness, ease of use, task alignment, and behavioral intention remaining consistently high across the sample.

Crucially, the study uncovered important disciplinary nuances. While the general utility of AI is universally recognized, non-STEM teachers reported significantly higher perceived ease of use and task match compared to their STEM teachers. This highlights a critical reality: current GenAI platforms excel at text generation for humanities tasks but still present friction when applied to the rigorous computational and analytical demands of engineering and science curricula.

Concurrently, teachers remain highly aware of the challenges accompanying AI integration, including operational friction, academic integrity concerns, and unpredictable output quality. The alignment between these reported challenges and the teachers' requests for concrete case repositories and ethical guidelines demonstrates that teachers are not resisting AI; rather, they are pragmatic adopters seeking well-designed institutional and technical support. Ultimately, this study challenges binary views of teachers as either resistant or blindly optimistic, providing a foundation for context-sensitive, discipline-specific strategies to enhance meaningful AI integration.

6.1 Implications

The findings of this study offer several important insights for policymakers, school leaders, professional development providers, and technology developers. Teachers' strong desire for clear policies and ethical guidance suggests that institutions must move beyond basic restrictions and offer practical frameworks for responsible AI use. These should cover academic integrity, privacy, and suggested ways to use AI effectively in planning and assessment. The high interest in real classroom examples suggests that teachers benefit more from concrete examples than general guidelines.

For training providers and developers, the results highlight the need to design support that fits teachers' real classroom needs. Particularly for the STEM and engineering education community, ed-tech developers must move beyond generic, natural-language chatbots. There is a pressing need to design domain-specific AI tools that can reliably handle complex algorithmic problem-solving, spatial reasoning, and coding validation without generating fiction. Furthermore, because many teachers still lack operational skills, so training should include both technical instructions and classroom strategies. Teachers also seem to prefer flexible support, like quick demos or self-paced resources, to traditional workshops. Developers, in turn, should focus on building user-friendly tools that reduce uncertainty and fit smoothly into teaching workflows. Institutions should also recognize teachers as active agents of change, encouraging a thoughtful and ethical AI use in their classrooms.

6.2 Limitations & Future Research

Several limitations of this study should be acknowledged, providing clear directions for future research. First, the use of convenience sampling via online platforms may reduce the generalizability of the results. Crucially, because the survey was distributed anonymously, there was no rigorous mechanism to independently verify respondents' professional identities. While participants self-reported their status as in-service teachers, the inability to officially authenticate this demographic data remains a notable limitation. Future research should apply stratified random sampling across specific institution levels and geographic regions, and incorporate explicit identity verification steps to ensure sample validity.

Second, as an exploratory descriptive study, the survey utilized concise, three-item subscales, which resulted in lower internal consistency (Cronbach's alpha) at the sub-construct level. Future studies should employ expanded, rigorously validated psychometric instruments to strengthen measurement reliability.

Third, certain behavioral metrics in this study were captured broadly. For instance, future research must disaggregate passive tolerance (e.g., allowing students to use AI for basic searches) from active pedagogical integration (e.g., recommending structured AI-assisted engineering design assignments) to accurately capture the depth of adoption.

Finally, the cross-sectional design reflects only one moment in time within a rapidly evolving technological landscape and relies entirely on self-reported data. Longitudinal studies, combined with qualitative classroom observations, interviews, and actual usage analytics, are necessary to understand how teachers' beliefs, decisions, and contexts relate to AI use in education.

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