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# Understanding Teachers' Adoption of AI Technologies: An Empirical Study from Chinese Middle Schools

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**Abstract:** The advancements in artificial intelligence (AI) technologies and the implementation of government policies are accelerating educational reform in China. In this context, understanding the critical factors influencing middle school teachers' adoption of AI technologies for classroom instruction is essential for fostering the deep integration of these technologies into teaching and improving teaching efficiency in middle schools. Grounded in the structural equation model (SEM) approach, this research integrates the Innovation Diffusion Theory, the Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT), and proposes a structural model comprising 10 latent variables. A measurement model is then developed for each latent variable, forming the basis of a survey questionnaire. Through empirical research using the questionnaires of 202 middle school teachers, a validated structural equation model with strong model fitting is established. The findings indicate that the most influential factors positively affecting teachers' willingness to use AI technologies, in descending order, are Interpersonal Relationships, Innovativeness, Mass Media, Compatibility, Perceived Usefulness, and Perceived Ease of Use. Similarly, factors positively influencing teachers' actual usage behavior, ranked by impact, include teachers' willingness, Facilitating Conditions, Career Aspiration, and Perceived Usefulness. Results involving the impact of teachers' Interpersonal Relationships can update the theoretical understanding of the factors driving the integration of AI into teaching, and be used to put forward specific directions such as social network embedding for actionable practice recommendations.

**Keywords:** AI technology; middle school teachers; willingness to use technology; influencing factors; structural equation model

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## 1. Introduction

As a representation of the widespread adoption of information technologies, the integration and application of these technologies in education have long been a focal point of concern within the academic field [1,2]. While governments worldwide place significant emphasis on innovative, technology-enabled education, a key factor in the successful implementation of such policies is the actual use of these technologies by teachers. Therefore, analyzing the factors that influence teachers' acceptance intentions and attitudes toward these technologies has become an important area of research, leading to valuable insights [3–5].

At the same time, a review of the dynamic development of related research reveals that scholars have seldom provided detailed descriptions of the evolving meaning of "educational technology" [6,7], despite the fact that research outcomes from different

periods have addressed various educational technologies. This gap has contributed to the emergence of the Technology Acceptance Model (TAM), developed during the information era, along with its extended models, such as UTAUT and UTAUT2, which have become the primary methodologies in this field.

Indeed, it is essential to recognize that as we transition from the informational era to the AI era, the connotation, degree of innovation, impact, value, and risks associated with technology are undergoing profound changes [8–10]. The current wave of intelligent technological innovations has begun to challenge decision-making behaviors and patterns. This trend is clearly evident in the field of educational technologies. The emerging AI teaching technologies refer to the various AI assistants, such as large language models based on the digitization of teaching systems, that can provide teachers with intelligent decision-making support regarding teaching, assist in accurately analyzing, evaluating, and optimizing teaching behaviors, and improve the effectiveness and efficiency of teaching. On the one hand, the value of AI technologies in enhancing efficient and personalized teaching is increasing significantly [11,12]. On the other hand, the scope, level of participation, and interactivity when applying these technologies are also expanding [13,14]. However, there remains limited research exploring teachers' willingness and attitudes toward accepting these innovative educational technologies [13].

In the context of the new era, encouraging teachers to actively embrace AI teaching technologies undoubtedly holds significant educational value. Before designing strategies for promotion, it is crucial to explore and understand the factors influencing teachers' willingness to adopt these specific innovations in AI teaching technologies for classroom instruction. This exploration is of great theoretical and practical importance.

In this study, we propose an influence analysis framework based on the Innovation Diffusion Model and the Technology Acceptance Model (TAM), using the structural equation model as the primary empirical research tool. We examine the potential factors influencing teachers' willingness and behaviors in adopting AI teaching technologies across three dimensions: Teacher Characteristics, Technological Characteristics, and Social Characteristics. This framework incorporates several latent variables, including teachers' Innovativeness, Career Aspiration, Perceived Usefulness, Perceived Ease of Use, and Compatibility of the AI teaching technologies, as well as Facilitating Conditions, Interpersonal Relationships, and external Mass Media. Among them, the consideration of teachers' Career Aspiration and the attributes of their Interpersonal Relationships highlights the novelty of this study.

## 2. Theoretical Foundations and Hypotheses

### *2.1. Technology Acceptance Model (TAM)*

The Technology Acceptance Model (TAM), proposed by Davis, is built upon the Theory of Reasoned Action and the Theory of Planned Behavior, integrating concepts from self-efficacy theory, expectancy theory, Diffusion of Innovations theory, and input–output theory [15]. The model suggests that users' Behavioral Intentions are determined by their attitudes toward usage and Perceived Usefulness, with Perceived Ease of Use having a significant influence on Perceived Usefulness. External variables in the model also play a crucial role in shaping users' Behavioral Intentions and actual adoption of the technology. TAM is widely used to predict individual acceptance of specific technologies and to understand the reasons behind technology adoption or rejection.

Venkatesh et al. developed the Unified Theory of Acceptance and Use of Technology (UTAUT) by integrating elements from TAM, the Theory of Reasoned Action, the Motivation Model, the Theory of Planned Behavior, the Combined TAM and TPB Model, the PC Utilization Model, Innovation Diffusion Theory (IDT), and Social Cognitive Theory [16]. This model includes four key variables: Performance Expectancy, Effort Expectancy, Social

Influence, and Facilitating Conditions, along with control variables such as gender, age, experience, and voluntariness, which influence these core variables.

In the field of educational research, TAM provides a fundamental methodological framework for analyzing teachers' willingness and behavior toward the adoption of educational technology [17,18].

### 2.2. Innovation Diffusion Theory (IDT)

Rogers and other scholars conducted a systematic study of innovation diffusion, leading to the development of the widely influential Innovation Diffusion Theory [19]. This theory proposes that the diffusion of innovations occurs in five distinct stages: knowledge, persuasion, decision, implementation, and confirmation. In the first stage, "knowledge", two key variables are identified: the recipient variable, which includes personal characteristics, social characteristics, and the perceived need for innovation, and the social system variable, which encompasses norms within the social system, tolerance for deviance, and the overall integration of the diffusion process. In the second stage, "persuasion", the "perceived characteristics of innovations" play a crucial role, including relative advantage, compatibility, complexity, and trialability.

Undoubtedly, for this research topic concerning teachers' willingness to adopt AI teaching technologies, the variables outlined in the first two stages of this model are highly relevant. The "recipient variable" inspired our dimension of "Teacher Characteristics", which is an observational dimension not directly addressed by TAM. Unlike TAM, which focuses on teachers' acceptance perspectives, IDT offers a comprehensive and independent third-party view on innovation diffusion [20].

IDT is particularly valuable for research on the diffusion of educational innovations. Anthony Jnr et al. [21] found that institutional structure, resource support, technological infrastructure, management strategies, and ethical considerations are key variables in predicting the diffusion of blended learning initiatives in higher education. Teo et al. [22] identified Ease of Use, Usefulness, attitudes, and Perceived Behavioral Control as significant determinants of university students' acceptance of MOOCs. Salajan [23] proposed the European Digital Education Area as a policy space and mechanism for integrating mainstream digital technologies within the European education and training system, advocating for its formal recognition as a policy priority to achieve coherence and coordination in digital education at the EU level.

### 2.3. Teachers' Acceptance of Intelligent Teaching Technology

In recent years, there has been a growing academic interest in artificial intelligence (AI) and its effective application in the teaching process [24]. Unlike information technologies for teaching assistance, which primarily help teachers deliver knowledge and information more conveniently and quickly, AI teaching technologies focus on analyzing the information within the teaching process and developing strategies to optimize teaching [25,26]. A summary of the main research on teachers' intentions, behaviors, and the factors influencing their use of AI teaching technologies is presented in Table 1.

Among these studies, TAM is the most widely adopted theoretical model, followed by SEM and UTAUT. Furthermore, under the theme of acceptance of AI teaching technologies, novel latent variables—such as Teacher's Trust [24,27], Subjective Norms [28,29], Anxiety [27,30], and Perceived Risk [13,31]—have emerged, alongside conventional variables like Performance Expectancy, Facilitating Conditions, Compatibility, Perceived Usefulness, and Perceived Ease of Use. These new variables have been shown to significantly impact teachers' decisions, reflecting the greater pressures and challenges posed by AI teaching technologies compared with traditional information technologies.

In addition, latent variables related to artificial intelligence literacy have also gained attention [28,32]. It is important to note that the latent variable of Social Influence has been frequently considered in relevant research [24,32]. However, there is a lack of in-depth analysis of this broad and influential factor.

**Table 1.** Past research on teachers' acceptance of intelligent teaching technology.

| Research | Aim | Theory/Model | Findings |
| --- | --- | --- | --- |
| [33] | Investigating college teachers' Behavioral Intention to adopt AI-assisted teaching systems | TAM, IDT | The complexity of AIATS positively affected Perceived Ease of Use by means of Perceived Time Cost, thereby influencing BI; sociocultural factors significantly impacted the adoption and promotion of AIATS in China. |
| [24] | Investigating acceptance of AI-powered ChatGPT as a tool for supporting metacognitive self-regulated learning among academics | TAM, SEM | A high acceptance of ChatGPT was significantly influenced by Personal Competency, Social Influence, Perceived AI Usefulness, enjoyment, trust, AI intelligence, positive attitude, and metacognitive self-regulated learning. |
| [27] | Understanding teachers' willingness to use artificial intelligence-based teaching analysis system | TAM, Fear of evaluation | Teachers' evaluation anxiety negatively affected PEU and teachers' willingness. Teaching efficacy and achievement goal orientations both had influences on evaluation anxiety. |
| [30] | Exploring the relationship between psychological factors and adoption readiness in teachers' attitudes toward AI-based assessment systems | UTAUT | Anxiety had a significant negative impact on the adoption readiness and attitude of university teachers; adoption readiness mediates the relationship between anxiety and attitude. |
| [28] | Exploring the factors influencing teacher education students' willingness to adopt AI technology for information-based teaching | TAM | The study underscored the pivotal role of AI literacy in influencing educators' acceptance of AI technologies, and the identified PU and artificial intelligence. Literacy was the primary factor affecting BI to use AI technologies. |
| [13] | Exploring teachers' attitudes and intentions towards intelligent MR devices | TAM, IDT | Innovation and relative advantage significantly and positively influenced teachers' attitudes toward using intelligent MR devices. |
| [29] | Investigating factors that predict teachers' intentions to utilize emerging technologies | PLS-SEM, DTPB | The antecedents to behavior: (a) teachers' Subjective Norms (peers and superiors) and (b) attitude (Compatibility and PU) were most influential in predicting BI to adopt and use emerging technologies. |
| [17] | Understanding continuous use intention of technology among higher education teachers in an emerging economy | TAM, UTAUT, TPACK, PLS-SEM | PEU, PU, SEE, and SI were key predictors of continuous use intention. While TPACK was influenced by FC and MAG, which exerted significant influence on PEU, PU, and SEE. |

**Table 1.** *Cont.*

| Research | Aim | Theory/Model | Findings |
| --- | --- | --- | --- |
| [26] | Reviewing the partnership of teachers and intelligent learning technology | Literature review | A majority of papers used either domain or learner models, suggesting that instructional decisions are mostly left to teachers. Model-based learning analytics can address some of the shortcomings of the field, like the meaningfulness and actionability of learning analytics tools. |
| [32] | Modeling English teachers' Behavioral Intention to use artificial intelligence in middle schools | UTAUT, TPACK | The EFL teachers were positive with regard to the measured factors. PE, SI, AIL-TK, and AI-TPACK had significant positive predictive power on BI, and EE, FC, and AI-TPK had indirect effects on BI. |
| [31] | Analyzing the adoption of artificial intelligence in higher education | UTAUT, SEM | Perceived Risk and Effort Expectancy had an impact on the attitude of the stakeholders of higher educational institutes in India to adopt AI. The Facilitating Conditions would also help the users to exhibit acceptable and favorable intentions to use AI in the higher education system. |

### *2.4. Hypothesis Development*

In summary, considering that in the intelligent era educational technology innovation—represented by AI technologies—has significantly different implications and denotations compared with the past, the opportunities and challenges faced by teachers vary depending on the stage of human development. The impact, value, and risks associated with teaching reform also differ. Therefore, it is essential to comprehensively examine teachers' willingness and behaviors toward applying this innovative, high-value, and high-barrier intelligent teaching technology.

Building on the considerations above, and drawing from the three dimensions of Teacher Characteristics, Technological Characteristics, and Social Characteristics, we have developed an influence analysis framework. This framework, which combines insights from TAM and its extended models, and is supported by the Innovation Diffusion Model, includes 10 latent variables, as illustrated in Figure 1.

Figure 1 illustrates our research design, depicting the relationships between these variables, which form the initial structural model of the structural equation model we developed. Based on this framework, we proposed 18 specific hypotheses, which were later validated and refined through subsequent empirical research.

#### 2.4.1. Influencing Factors and Hypotheses About Technology Characteristics

Perceived Usefulness, Perceived Ease of Use, and Compatibility are used to describe the technological characteristics in our model.

Perceived Usefulness (PU) and Perceived Ease of Use (EU) are core latent variables in TAM [34], and we have retained these two variables in our structural model.

Perceived Usefulness refers to the degree to which potential users believe that using a technology will enhance their job performance. Empirical studies in various technology acceptance scenarios have confirmed the actual impact of Perceived Usefulness [35]. In this study, Perceived Usefulness denotes teachers' perceived value of using AI technologies in their teaching practice.

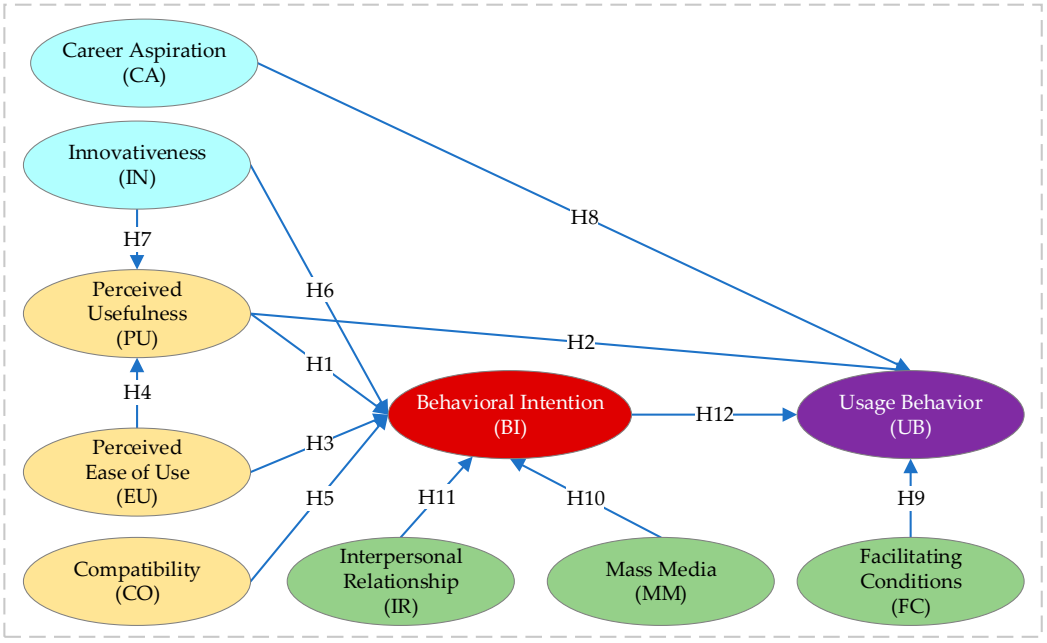



**Figure 1.** The proposed structural model.

Perceived Ease of Use refers to the degree of difficulty that potential users expect to encounter when using a particular technology. Similar to Perceived Usefulness, the real impact of Perceived Ease of Use has been validated in various scenarios [36]. As noted earlier, the application of AI teaching technologies presents high barriers and significant challenges for teachers [13,26]. Middle school teachers, in particular, face heavy teaching workloads, alongside administrative duties. Therefore, we are particularly interested in the practical implications of Perceived Ease of Use within the context of this study.

Based on this consideration, we proposed the following hypotheses:

**H1.** *Perceived Usefulness has a significant positive impact on middle school teachers' willingness to apply AI teaching technologies.*

**H2.** *Perceived Usefulness has a significant positive impact on middle school teachers' actual application of AI teaching technologies.*

**H3.** *Perceived Ease of Use has a significant positive effect on middle school teachers' willingness to apply AI teaching technologies.*

**H4.** *Perceived Ease of Use has a significant positive effect on AI teaching technologies' Perceived Usefulness.*

Given the high degree of innovation in AI teaching technologies, which present certain barriers and challenges for teachers, we introduced the latent variable of Compatibility, building on the principles of IDT [37].

Compatibility reflects Rogers' theory regarding the degree to which innovations align with the cognitive attributes of potential adopters. In this paper, Compatibility refers to the extent to which teachers perceive a match between innovative teaching technologies and their existing experiences, technical proficiency, and teaching requirements. If middle school teachers' technical foundations align with innovative teaching technologies, they are more likely to adopt these innovations [38]. Based on this, we propose the following hypothesis:

**H5.** *Compatibility has a significant positive impact on middle school teachers' willingness to apply AI teaching technologies.*

#### 2.4.2. Influencing Factors and Hypotheses About Teacher Characteristics

Innovativeness and Career Aspiration are used to describe Teacher Characteristics in the context of applying AI teaching technologies. Drawing inspiration from the "recipient variable" in the Innovation Diffusion Model [39], we conducted on-site interviews with teachers to understand their initial responses to educational innovative technologies. Based on these interviews, we developed the following latent variables.

Among these, Innovativeness represents teachers' openness to new ideas and technologies. Numerous studies have identified Innovativeness as a key influencing factor [40,41]. In this paper, Innovativeness reflects teachers' attitudes and may significantly impact their perceptions of the usefulness of AI technologies. Thus, we propose two hypotheses:

**H6.** *Middle school teachers' Innovativeness has a significant positive impact on their willingness to apply AI teaching technologies.*

**H7.** *Middle school teachers' Innovativeness has a significant positive impact on their Perceived Usefulness of AI teaching technologies.*

The latent variable Career Aspiration represents an intrinsic motivation for teachers to apply AI technologies. Self-Determination Theory suggests that both social-environmental and individual intrinsic motivations contribute to personal development [42]. In middle schools, teachers not only aim to enhance their teaching competence and effectiveness, as reflected in the performance expectancy variable of the UTAUT model [43] but also seek career advancements such as promotions, official evaluations, and salary increases [44,45]. We believe that teachers' Career Aspirations may influence their perceptions of the usefulness of AI technologies, thus enhancing their willingness to adopt these technologies. Therefore, we propose the following hypotheses:

**H8.** *Career Aspiration has a significant positive impact on middle school teachers' actual application of AI teaching technologies.*

#### 2.4.3. Influencing Factors and Hypotheses About Social Characteristics

The dimension of social characteristics primarily includes three latent variables: Facilitating Conditions, Mass Media, and Interpersonal Relationships.

According to IDT, Facilitating Conditions significantly influence the adoption rate of innovations, especially through the promotion of external environments [46]. In China, there is a growing consensus to empower education with AI technologies. Educational management departments at various levels are implementing policies and measures to promote the digital transformation of education and teaching [47].

These prevailing trends are creating numerous Facilitating Conditions for teachers to adopt AI technologies. In this study, Facilitating Conditions primarily refer to the encouragement and support from schools and educational authorities for applying AI technologies, as well as the availability of infrastructure, hardware, and software resources. Based on this, we propose the following hypothesis:

**H9.** *Facilitating Conditions have a significant positive impact on middle school teachers' actual application of AI teaching technologies.*

Mass Media represents the channels and mechanisms through which innovations in AI teaching technologies are disseminated, reflecting their application in the education sector beyond individual teachers [48]. As an effective tool for diffusion, Mass Media is characterized by its broad reach and unidirectional control. In contemporary China, the rise of short video platforms has further expanded the avenues for information dissemination. The flow and spread of information through these channels can significantly influence teachers' cognitive attitudes toward intelligent teaching technology innovations, as well as their willingness to adopt them [49]. Based on this, we propose the following hypothesis:

**H10.** *Mass Media has a significant positive impact on middle school teachers' willingness to apply AI teaching technologies.*

Interpersonal Relationships reflect the influence of teachers' social networks on their use of AI technologies in teaching. The teacher community, as a social system, shares many common characteristics, making Interpersonal Relationship channels within this group particularly effective in persuading individuals to accept innovations [50]. Therefore, as members of a school's social network, teachers' behaviors are inevitably influenced by the strength of Interpersonal Relationships within the school [51]. In other words, the quality and strength of teachers' Interpersonal Relationships will impact their willingness to adopt technology. Based on this, Hypothesis 11 is proposed:

**H11.** *Interpersonal Relationships has a significant positive impact on middle school teachers' willingness to apply AI teaching technologies.*

Additionally, it is widely recognized that teachers' willingness to apply technologies has a significant positive impact on their actual application behavior, which forms Hypothesis 12 of this study:

**H12.** *Middle school teachers' Behavioral Intention has a significant positive impact on their usage behavior.*

## 3. Methodology

The following quantitative study is divided into two parts, measurement and data analysis.

### *3.1. Measurement*

#### 3.1.1. Measurement Model Design

First, to complete the structural equation modeling, a measurement model must be constructed for the structural model illustrated in Figure 1, along with its corresponding hypotheses. The measurement model is presented in the form of a questionnaire, where each latent variable typically consists of three or more measurement items. These items serve as observable indicators for the latent variables, which are treated as common factors. The development of our questionnaire integrates elements from the Innovation Diffusion Theory (IDT), interviews with teachers, and existing questionnaire scales, as shown in Table 2.

**Table 2.** Survey questions of our measurement model.

| Construct | Code | Survey Item | Reference |
| --- | --- | --- | --- |
| Innovativeness (IN) | IN1 | I often like to try new technologies in teaching | [40,52] |
| | IN2 | I often keep an eye on the latest developments and applications of new teaching technologies. | |
| | IN3 | I'm willing to accept new educational concepts in teaching. | |
| | IN4 | I'm willing to change my teaching methods in teaching. | |
| Career Aspiration (CA) | CA1 | Using AI teaching technologies provides me with a greater sense of teaching accomplishment. | [43,44] |
| | CA2 | Using AI teaching technologies in teaching can enhance my chances of getting a salary increase or promotion. | |
| | CA3 | Using AI teaching technologies in teaching is facilitating my professional development. | |
| Perceived Usefulness (PU) | PU1 | I think using AI teaching technologies can improve my teaching efficiency. | [38,53] |
| | PU2 | I think using AI teaching technologies can enhance the teaching efficiency. | |
| | PU3 | I think using AI teaching technologies can boost students' classroom participation. | |
| Perceived Ease of Use (EU) | EU1 | My interaction with AI teaching technologies in teaching is clear and understandable in my mind. | [34,54] |
| | EU2 | It doesn't take me a long time to remember how to use AI teaching technologies. | |
| | EU3 | I think it's easy to incorporate AI teaching technologies into teaching design. | |
| Compatibility (CO) | CO1 | I think my ability to use technology matches the requirements of AI teaching technologies. | [37,55] |
| | CO1 | I believe using AI teaching technologies aligns with my preferred teaching style. | |
| | CO3 | I think using AI teaching technologies meets my teaching needs. | |
| Facilitating Conditions (FC) | FC1 | My school strongly supports teachers in applying AI teaching technologies. | [46,56] |
| | FC2 | My school can regularly offer trainings on using AI teaching technologies to assist teaching. | |
| | FC3 | I think the exam-oriented education hinders me from using AI teaching technologies. | |
| | FC4 | My school can provide corresponding software and hardware facilities, and conduct regular maintenance and upgrades. | |
| Mass Media (MM) | MM1 | I often read reports on the current application of AI teaching technologies being pushed on TV, news websites, or self-media platforms. | [48,57] |
| | MM2 | I often pay attention to the news regarding the application of AI teaching technologies on social media platforms. | |
| | MM3 | Technology companies that empower teaching with intelligent technology often come to my school to do promotional activities. | |
| Interpersonal Relationships (IR) | IR1 | School leaders think that I should use AI teaching technologies. | Added item |
| | IR2 | My colleagues think that I should use AI teaching technologies. | |
| | IR3 | Parents and students think that I should use AI teaching technologies. | |

#### 3.1.2. Sample and Data Collection

This study targeted middle school teachers for the survey, utilizing a combination of paid sample services from the *Wenjuanxing* platform (www.wjx.cn) and the research team's social networks for dissemination. The survey was conducted between March and May

2024. A total of 238 samples were collected, and 202 valid questionnaires were obtained, yielding a valid response rate of 85%.

The basic demographic information of the sample is shown in Table 3. The demographic characteristics are as follows: the male-to-female teacher ratio is approximately 4:6, which aligns with the gender distribution of middle school teachers in China. In terms of teaching experience, competent teachers (3–5 years) account for 32.2%, and mature teachers (6–15 years) comprise 45%. This suggests that a substantial proportion of the teachers in the sample are at the competent level or above. Regarding the geographical distribution of the teachers' schools, the East China region holds the largest share at 45%, followed by Central and South China at 17.3%, and North China at 15.8%. As for educational background, 78.7% of teachers hold a bachelor's degree and 20.7% have a master's degree. These figures align closely with the current educational background profile of middle school teachers in China. In terms of the nature of the schools, 82.7% of the teachers work in public schools, while 17.3% are employed in private schools. Regarding the subjects taught, teachers of the three major subjects—Chinese, foreign languages, and mathematics—account for 74.3% of the sample, with the remaining 25.7% teaching other subjects.

**Table 3.** Demographic profile of participants.

| Item | Options | Frequency | Percentage | Item | Options | Frequency | Percentage |
|---|---|---|---|---|---|---|---|
| Gender | Male | 79 | 39.1 | Teaching Experience | <3 years | 79 | 39.1 |
| | Female | 123 | 60.9 | | 3–5 years | 123 | 60.9 |
| Education background | Doctor | 2 | 1 | | 6–15 years | 91 | 45 |
| | Master | 41 | 20.3 | | >15 years | 15 | 7.4 |
| | Bachelor | 159 | 78.7 | Proficiency Level | Very proficient | 76 | 37.6 |
| Region | North China | 32 | 15.8 | | Proficient | 104 | 51.5 |
| | Northeast China | 17 | 8.4 | | Average | 19 | 9.4 |
| | East China | 91 | 45 | | Not very proficiency | 3 | 1.5 |
| | Central South China | 35 | 17.3 | subjects | Chinese | 80 | 39.6 |
| | Southwest China | 16 | 7.9 | | Foreign Language | 21 | 10.4 |
| | Northwest China | 11 | 5.5 | | Mathematics | 49 | 24.3 |
| Using Frequency | Every class | 125 | 61.9 | | Science | 25 | 12.4 |
| | Frequently | 45 | 22.3 | | History and Society | 8 | 4 |
| | Sometimes | 10 | 5 | | Thought Morality | 6 | 3 |
| | Occasionally | 22 | 10.9 | | Information Technology | 5 | 2.5 |
| School nature | Public School | 167 | 82.7 | | Others | 8 | 4 |
| | Private School | 35 | 17.3 | | | | |

### *3.2. Data Analysis*

The second part of the study involved conducting an empirical analysis of the proposed hypotheses based on the collected data. In this section, we first performed reliability

and validity analyses. Then, we used the structural equation modeling software AMOS 26.0 to test and refine the structural model shown in Figure 1. Additionally, we tested the 12 hypotheses outlined in the initial structural model.

## 4. Results

### *4.1. Reliability and Validity Analysis*

To ensure the reliability and validity of the collected data, reliability and validity analyses of the questionnaire were conducted before the empirical study.

#### 4.1.1. Reliability

This study used Cronbach's $\alpha$ coefficient to assess the reliability of the questionnaire, using SPSS 23.0 software. Generally, a Cronbach's $\alpha$ value above 0.6 is considered acceptable for reliability [58]. The results show that for the overall questionnaire and the 10 latent variables (Perceived Usefulness, Perceived Ease of Use, Compatibility, Innovativeness, Career Aspiration, Facilitating Conditions, Mass Media, Interpersonal Relationships, Behavioral Intention, and Usage Behavior), the Cronbach's $\alpha$ values range from a minimum of 0.621 to a maximum of 0.912. All values exceed the 0.6 threshold, indicating good internal consistency of the questionnaire.

#### 4.1.2. Validity

Validity examines the degree of alignment between the actual results and the research framework. In this study, the main types of validity analyzed are content validity and construct validity.

Content validity refers to the extent to which a measurement tool reflects the domain of the concept being studied, ensuring the tool is appropriate and the content is representative. In this study, the scale and measurement variables were developed based on a comprehensive review of the existing research literature in the field. The validity of the scale has already been confirmed in previous studies, providing a solid theoretical foundation for establishing content validity in this research.

Construct validity refers to the extent to which measurement items logically relate to constructs based on the underlying theory, evaluating whether observed data can support a theoretical assumption, classification, or hypothesis. Convergent validity is a key indicator of construct validity.

The verification of construct validity involves extracting the main factors. First, SPSS 23.0 was used to calculate the Kaiser–Meyer–Olkin (KMO) value and the significance (sig.) of Bartlett's test of sphericity to assess whether the sample data was suitable for factor analysis. The results showed that the KMO values for the overall questionnaire and each scale were all above 0.6, and the *p*-values for Bartlett's test were all less than 0.001, indicating significant correlations among the measurement items. Therefore, the scale is suitable for factor analysis, confirming its construct validity.

For the construct validity of the scale, various parameters were calculated, as shown in Table 4. The factor loading coefficient values represent the correlation between latent variables and observed variables (measurement questions). If an item has a standardized loading coefficient greater than 0.7, it indicates a strong correlation. Composite Reliability (CR) and Average Variance Extracted (AVE) are used to evaluate convergent validity. Typically, if the AVE exceeds 0.5 and the CR exceeds 0.7, convergent validity is considered high. The results indicate that the factor loading (FL) for each measurement item ranges from 0.647 to 0.815. The AVE values and CR values for each latent variable range from 0.501 to 0.608 and 0.750 to 0.821, respectively. Since all CR values exceed 0.7 and all AVE values exceed 0.5, the questionnaire demonstrates good convergent validity.

**Table 4.** Validity analysis (*N* = 202).

| Factors | Code | FL (Factor Loading) | CR (Composite Reliability) | AVE (Average Variance Extracted) |
|---|---|---|---|---|
| | | **>0.6** | **>0.7** | **>0.5** |
| Innovativeness (IN) | IN1 | 0.736 | 0.821 | 0.535 |
| | IN2 | 0.712 | | |
| | IN3 | 0.723 | | |
| | IN4 | 0.755 | | |
| Career Aspiration (CA) | CA1 | 0.749 | 0.801 | 0.574 |
| | CA2 | 0.705 | | |
| | CA3 | 0.815 | | |
| Perceived Usefulness (PU) | PU1 | 0.73 | 0.750 | 0.501 |
| | PU2 | 0.66 | | |
| | PU3 | 0.732 | | |
| Perceived Ease of Use (EU) | EU1 | 0.693 | 0.771 | 0.529 |
| | EU2 | 0.747 | | |
| | EU3 | 0.641 | | |
| Compatibility (CO) | CO1 | 0.703 | 0.774 | 0.533 |
| | CO2 | 0.759 | | |
| | CO3 | 0.728 | | |
| Facilitating Conditions (FC) | FC1 | 0.774 | 0.784 | 0.550 |
| | FC2 | 0.796 | | |
| | FC3 | 0.647 | | |
| Mass Media (MM) | MM1 | 0.802 | 0.756 | 0.608 |
| | MM2 | 0.782 | | |
| | MM3 | 0.757 | | |
| Interpersonal Relationship (IR) | IR1 | 0.711 | 0.781 | 0.544 |
| | IR2 | 0.740 | | |
| | IR3 | 0.761 | | |

### *4.2. Fitting and Modification of the Structural Model*

Next, supported by the data from the collected questionnaires, this study evaluated and revised the structural model shown in Figure 1. The evaluation was based on six key parameters used to assess model fit: the chi-square to degrees of freedom ratio ($\chi^2$/df), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Root Mean Square Error of Approximation (RMSEA), Normed Fit Index (NFI), and Comparative Fit Index (CFI). These parameters were compared with their ideal benchmark values to evaluate the model's goodness of fit. After four rounds of evaluation and modifications, the final structural model was obtained and is shown in Figure 2 and Table 5, respectively.

The above figure and table show that all the path coefficients are positive, and all 12 hypotheses are supported.

In addition, R-squared values describe the relationship between exogenous variables (e.g., Perceived Usefulness) and endogenous variables (e.g., Behavioral Intention), that is, the degree to which the exogenous variables explain the variance of the endogenous variables. In Figure 2, Innovativeness and Perceived Ease of Use together accounted for 67.3% of the variance in Perceived Usefulness. The collective impact of Perceived Usefulness, Innovativeness, Perceived Ease of Use, Compatibility, Interpersonal Relationship, and Mass Media accounted for 91.0% of the variance in Behavioral Intention. Behavioral Intention, Perceived Usefulness, and Career Aspiration accounted for 90.1% of the variance in Usage Behavior. Compared with other variables, Perceived Usefulness had the least

explained variance, at 67.3%, which implies that there may be other factors influencing Perceived Usefulness.

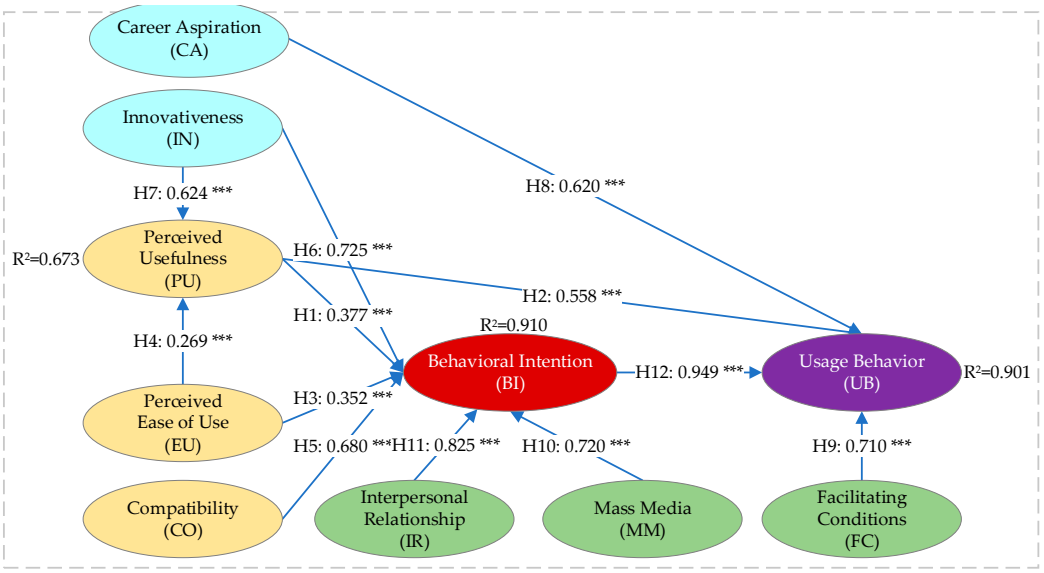



**Figure 2.** Revised Structural Equation Model. (*** = $p < 0.001$).

**Table 5.** Results of hypothesis testing.

| Hypothesis | Correlated Paths | Estimate | S.E. | C.R. | *p* Value | Result |
|---|---|---|---|---|---|---|
| H1 | BI <--- PU | 0.377 | 0.200 | 7.828 | *** | Support |
| H2 | UB <--- PU | 0.558 | 0.041 | 4.519 | *** | Support |
| H3 | BI <--- EU | 0.352 | 0.018 | 5.301 | *** | Support |
| H4 | PU <--- EU | 0.269 | 0.245 | 5.066 | *** | Support |
| H5 | BI <--- CO | 0.680 | 0.176 | 6.579 | *** | Support |
| H6 | BI <--- IN | 0.725 | 0.252 | 5.23 | *** | Support |
| H7 | PU <--- IN | 0.624 | 0.039 | 5.244 | *** | Support |
| H8 | UB <--- CA | 0.620 | 0.126 | 6.239 | *** | Support |
| H9 | UB <--- FC | 0.710 | 0.123 | 4.328 | *** | Support |
| H10 | UB <--- MM | 0.720 | 0.195 | 6.898 | *** | Support |
| H11 | UB <--- IR | 0.825 | 0.182 | 6.624 | *** | Support |
| H12 | UB <--- BI | 0.949 | 0.156 | 4.811 | *** | Support |

(*** = $p < 0.001$)

The fit parameters of the revised model are presented in Table 6. These values indicate that the revised model demonstrates a good and acceptable fit to the data.

**Table 6.** Model fit indices.

| Fit Indices | χ2/df | GFI | AGFI | RMSEA | NFI | CFI |
|---|---|---|---|---|---|---|
| Benchmark | <3 | >0.8 | >0.8 | <0.08 | >0.8 | >0.8 |
| Results | 1.852 | 0.919 | 0.906 | 0.065 (90% CI: 0.064–0.066) | 0.926 | 0.819 |

## 5. Discussion

As educational technology continues to evolve, with new innovations, challenges, and even risks emerging, this paper focuses on understanding middle school teachers' willingness and behavior toward using AI teaching technologies. We developed a framework to explore the influencing factors across three dimensions: Teacher Characteristics, Technology Characteristics, and Social Characteristics, and built a structural model with 10 latent

variables. Using this framework, we designed a measurement model and conducted an empirical study with Structural Equation Modeling (SEM). The results of the empirical study show that most of our initial hypotheses were supported:

### 5.1. Dimension of Teachers Characteristics

Firstly, in terms of teacher characteristics, this research examines how teachers' Innovativeness and Career Aspirations affect their willingness to use and the actual usage of the technology. According to the results of the final structural model, teachers' Innovativeness has a strong positive impact on their willingness to use technology, with a path coefficient of 0.725. Innovativeness also significantly influences the Perceived Usefulness of technology, with a path coefficient of 0.624. Career Aspirations, on the other hand, have a positive impact on teachers' actual usage behavior, with a path coefficient of 0.645.

The findings suggest that Innovativeness has a more substantial impact than Career Aspirations. This highlights the importance of teachers' personal attitudes toward new technologies. In other words, teachers' views on technology—rather than external incentives like salary or performance—play a more significant role in their willingness to adopt it. When teachers stay informed about developments in intelligent education technologies and embrace emerging educational ideas, they are more likely to see the value in using such technologies and be motivated to integrate them into their teaching. Furthermore, when the use of these technologies can positively influence both teachers' professional reputation and tangible factors like salary, it can further boost their willingness to adopt and actively use them.

### 5.2. Dimension of Technology Characteristics

Secondly, this study also examines how the characteristics of AI teaching technologies influence middle school teachers' willingness to use and actual usage behavior. This influence is analyzed across three main factors: Perceived Usefulness, Perceived Ease of Use, and Compatibility. According to the final structural model:

Perceived Usefulness, Perceived Ease of Use, and Compatibility all have a strong positive impact on teachers' willingness to use AI technologies, with path coefficients of 0.377, 0.352, and 0.680, respectively.

Perceived Usefulness also has a significant positive effect on teachers' actual usage behavior, with a path coefficient of 0.558.

Notably, Compatibility has the greatest impact on teachers' willingness to use technology. This suggests that, when it comes to adopting intelligent teaching tools, teachers prioritize how well the technology integrates with their teaching practices and addresses their specific needs. If the technology can enhance teaching efficiency, improve learning outcomes, and align with teachers' teaching objectives, they are more likely to adopt it.

Furthermore, the Perceived Ease of Use of the technology positively affects its Perceived Usefulness. This is particularly relevant given the busy schedules of middle school teachers, who often lack the time to deeply learn new technologies or overhaul their teaching plans. Therefore, the more user-friendly and intuitive a technology is, the more likely teachers are to adopt it.

In conclusion, improving factors like Perceived Usefulness, Ease of Use, and Compatibility can significantly boost teachers' willingness to incorporate AI technologies into their teaching.

### 5.3. Dimension of Social Characteristics

Thirdly, in terms of social characteristics, this research investigates the influence of Facilitating Conditions, Mass Media, and Interpersonal Relationships on middle school

teachers' willingness to use and actual usage behavior. According to the results from the final structural model:

Both Mass Media and Interpersonal Relationships have a highly significant positive impact on teachers' willingness to use AI technologies for teaching, with path coefficients of 0.720 and 0.825, respectively.

Facilitating Conditions have a highly significant positive impact on actual usage behavior, with a path coefficient of 0.710.

Among these social characteristics, Interpersonal Relationships exert the most significant influence on teachers' willingness and usage behavior. Interviews and literature reviews suggest that teachers' social circles are often relatively homogeneous, meaning that their colleagues and friends can strongly influence their decisions to adopt new technologies. Additionally, Mass Media and Facilitating Conditions also play a vital role in shaping teachers' attitudes and behaviors. With the growth of online media, teachers now have greater access to information about AI technologies, which boosts their willingness to use these tools. Furthermore, the provision of favorable policies and adequate hardware support from schools is closely related to teachers' technology adoption.

In this study, the role of Interpersonal Relationships and Facilitating Conditions is largely framed within the school context. Support from school leaders, colleagues, parents, and students, as well as the availability of educational resources, significantly enhances teachers' willingness to use AI teaching technologies, which, in turn, influences their actual usage behavior.

Finally, it is noteworthy that middle school teachers' willingness to use AI teaching technologies has a highly significant positive impact on their actual usage behavior, with the highest path coefficient of 0.949 in the model. This highlights that increasing teachers' willingness to adopt these technologies is a key factor in promoting their actual use.

## 6. Limitations and Future Research

This study has several limitations. First, in terms of sample data collection and quantity, this study mainly distributed questionnaires through the researchers' friends and the *Wenjuanxing* platform. A total of 202 valid questionnaires were obtained. This quantity only meets the minimum sample size requirement, and at the same time restricts more possibilities for deep analysis. Therefore, in subsequent studies, we will increase the sample size to ensure the quality of the survey data, and provide a more scientific and accurate data foundation for subsequent empirical research.

Second, in terms of constructing the structural model, this study integrates multiple models, including the Innovation Diffusion Model, the Technology Acceptance Model and other models, and summarizes three dimensions that influence teachers' willingness to use AI teaching technologies. However, the factors influencing teachers' willingness are the comprehensive result of multiple aspects. The eight latent variables proposed in this study cannot cover all variables either. For example, implicit influencing factors such as educational policy restrictions and teachers' work pressure have not been measured by our questionnaires. In addition, it is an important future direction to provide a more comprehensive description of teachers' social attributes and introduce the network embeddedness of teachers. Therefore, our subsequent research will continue to explore more comprehensive latent variables and continuously improve the explanatory power of the research model.

## 7. Conclusions

Compared with educational technology during the information age, AI teaching technology will not only facilitate the convenient dissemination of information but, more

importantly, it will assist teachers in analyzing teaching data and proposing suggestions and implementation plans for optimizing teaching. This means that the connotations of educational technology has undergone significant changes in the era of artificial intelligence. Against this backdrop, this paper expands the descriptive perspective of teachers' characteristics from purely personal attributes to social attributes and further explores the acceptance issues of middle school teachers towards the use of AI technology to assist teaching. Based on TAM and IDT, this study refers to research achievements in the acceptance of information-based educational technology, and at the same time takes into account the impact of the new characteristics of AI teaching technology on teachers. The findings indicate that the most influential factors positively affecting teachers' willingness to use AI technologies, in descending order, are Interpersonal Relationships, Innovativeness, Mass Media, Compatibility, Perceived Usefulness, and Perceived Ease of Use. Similarly, factors positively influencing teachers' actual usage behavior, ranked by impact, include teachers' willingness, Facilitating Conditions, Career Aspiration, and Perceived Usefulness. Additionally, Perceived Usefulness directly enhances application behavior.

These findings possess both theoretical and practical values. The expansion of teachers' social attributes has not been explicitly addressed in previous studies, which is also a theoretical contribution of this research. This enables the research results to not only explain the influencing factors and relevant relationships at the "why" level but also to point out specific and feasible directions for promoting the willingness and behavior of middle school teachers to apply AI teaching technology at the "how" level. In practice, these findings can provide directional guidance for designing incentive policies to encourage middle-school teachers to apply AI teaching technology. For example, we suggest that policy designers consider cultivating the personal social networks of teachers related to AI teaching technology from the perspective of network embeddedness, which will utilize the positive value of teachers' social relationships.

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