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# INTEGRATING AI IN PRESCHOOL TEACHER EDUCATION: THE MEDIATING ROLE OF SELF-EFFICACY IN HEALTH EDUCATION AND THE MODERATING EFFECT OF TECHNOLOGICAL PROFICIENCY

**Qian Wang,**
**Qingyun Li,**
**Xinmian Cui,**
**Yanfei Xu,**
**Nina Wang,**
**Mengyan Wang**

**Abstract.** *Artificial Intelligence (AI) has the potential to transform preschool teacher education, particularly in the domain of health education, yet its effective integration remains underexplored in socioeconomically diverse regions. Understanding the psychological and technical factors that influence AI adoption is essential for improving early childhood education outcomes. This study examines the mediating role of self-efficacy and the moderating effect of technological proficiency in the relationship between AI integration and teaching effectiveness among preschool teachers. A mixed-methods approach was employed, involving 475 preschool teachers from Henan Province, China. Data were gathered using validated survey instruments and semi-structured interviews. The results revealed that AI integration positively influences teaching effectiveness, primarily through increased teacher confidence. Technological proficiency also plays a supporting role in enhancing instructional effectiveness. These findings highlight the importance of targeted training, equitable access to AI tools, and professional development programs that foster teacher readiness and confidence in adopting AI into early childhood education.*

**Keywords:** *AI integration in education, preschool teacher training, self-efficacy, technological proficiency, teaching effectiveness*

**Qian Wang**
*University of Malaya, Malaysia*
**Qingyun Li**
*University of Science Malaysia, Malaysia*
**Xinmian Cui**
*Experimental Kindergarten of Erqi District, P. R. China*
**Yanfei Xu**
*University of Malaya, Malaysia*
**Nina Wang**
*Guangdong University of Petrochemical Technology, P. R. China*
**Mengyan Wang**
*University of Malaya, Malaysia*

## Introduction

### *Background and Significance*

The rapid advancements in artificial intelligence (AI) have positioned it as a transformative force in various domains, including education. Early childhood education, particularly in health and foundational development, requires innovative tools to engage and equip teachers with essential skills (Frenk et al., 2010; Jalongo, 2021). AI offers potential solutions by providing interactive, adaptive, and data-driven methodologies to enhance learning experiences for both students and educators (Ahmad et al., 2024; Kabudi et al., 2021; Strielkowski et al., 2025). Experiences with AI integration in education throughout the world have shown that it can assist with administrative work, tailor learning paths, and guide teacher choices (Jin et al., 2023; Luckin & Cukurova, 2019). The readiness and capacity of educators to utilize these tools effectively, however, are critical to successful integration (Hew & Brush, 2007; Lawless & Pellegrino, 2007).

Preschool education, being foundational, is vital for cognitive, social, and physical development (Kohlberg, 1968; PedroStork & Sanders, 2008). In Henan, China, a region marked by a blend of urban and rural educational landscapes, the adoption of AI in teacher education programs offers an opportunity to bridge resource disparities and improve the quality of health education. Health education, focusing on topics like nutrition, hygiene, and mental well-being, serves as a critical area where AI can amplify content delivery and engagement. However, realizing this potential requires addressing factors such as teachers' self-efficacy and technological proficiency, which directly impact the adoption and effectiveness of AI tools in education.



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Preschool education is fundamental to children's physical, social, and cognitive development (Kohlberg, 1968; PedroStork & Sanders, 2008). Adopting AI in teacher education programs offers an excellent way to alleviate resource gaps and enhance the quality of health education in Henan, China, where the urban and rural educational environments coexist. Health education on subjects like diet, cleanliness, and mental health may be a crucial area where AI may improve content and engagement. However, given that these qualities have a significant impact on the acceptance and usefulness of AI technologies in education, improvements in things like teachers' technological ability and self-confidence are necessary for that to happen.

*Context: Henan, China*

The most populated province in central China, Henan offers a wide range of socioeconomic environments in addition to a diversified population. For this reason, it may be considered one of the most important areas for undertaking any type of study related to education. Preschool education in Henan has advanced significantly in recent years as a result of increased investment in this sector and the city's fast urbanization (Cheng et al., 2023). Nevertheless, there are still several drawbacks, such as inadequate resources, disparities in technology infrastructure, and significant disparities between urban and rural educational institutions (Salemink et al., 2017).

Therefore, Henan's decision to include AI into teacher training programs is a calculated step to address the current issues. AI technologies have the potential to assist educators in overcoming resource constraints and enhancing their efficacy in delivering comprehensive health education. However, Henan's educational system has only just begun to integrate these skills, so further study is needed to determine their efficacy and suitability.

*Problem Statement*

Even while AI has the greatest potential to change teaching methods, its application to preschool teacher training is still mainly untapped, particularly in socioeconomically varied areas like Henan. One of the most crucial but often overlooked facets of early childhood education is health education, which calls for creative teaching methods to keep students' interest and hold it. Lack of adequate technological skills and differences in educators' levels of self-efficacy are some of the barriers to incorporating AI into teacher preparation (Yang et al., 2024; Melweth et al., 2024). By examining the mediating function of self-efficacy and the moderating function of technological competency in AI integration inside Henan preschool teacher education programs, the current study attempts to close these gaps.

The study aimed to examine how AI can be effectively integrated into preschool teacher education in Henan, with a specific focus on health education, and to explore the roles of self-efficacy and technological proficiency in this process.

**Related Work**

*Artificial Intelligence in Education*

The focus of AI technology has now shifted to education, where they are beginning to alter teacher development. They offer methods for intelligent teaching, automating feedback systems, and improving individualized experiences through adaptable platforms (Castro et al., 2024; Kaswan et al., 2024; Lin et al., 2023). Additionally, early childhood education procedures, which inherently call for dynamic and interactive teaching methods, greatly benefit from these systems. By offering accurately replicated training scenarios and real-time feedback on teaching methods and approaches, AI-powered systems that use virtual assistants and simulations might improve teacher preparation (Dai & Ke, 2022; Mirchi et al., 2020).

*AI in Preschool Education*

The foundation for lifetime learning is laid by preschool education; hence, this field benefits greatly from AI applications (Su & Zhong, 2022). AI-powered systems enhance interactive learning by gamifying health education, enhancing cognitive abilities in young students, and narrating stories (Dighliya, 2025). For instance, using simulations, educators might "practice" presenting health education sessions with different emphasis on mental health, nutrition, and hygiene (DiMaria et al., 2014). Preschool AI in Henan, China, has thus far demonstrated promise in

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addressing urban-rural inequities since all students have equal access to high-quality teaching tools (Zheng et al., 2023). The application of AI in preschool teacher training is still in its infancy; further research is needed to determine its efficacy and scalability.

### *Self-Efficacy in Education*

Self-efficacy, defined as an individual's belief in their ability to execute tasks successfully (Bandura, 1997), plays a pivotal role in teacher effectiveness. Teachers with high self-efficacy are more likely to adopt innovative teaching strategies, such as AI tools, and to persist in the face of challenges (Sharma & Saini, 2022; Wang et al., 2021). Research indicates that self-efficacy not only impacts the adoption of technology but also enhances classroom management, lesson delivery, and student engagement (Xu et al., 2024; Doo et al., 2020).

In the context of health education, self-efficacy enables teachers to confidently deliver critical lessons on nutrition, hygiene, and physical activity. Teachers with higher self-efficacy tend to use engaging methods, such as interactive storytelling or gamified exercises, to impart health knowledge. The integration of AI tools can enhance this process by providing tailored content and supporting teachers with real-time analytics on student understanding.

### *Technological Proficiency and Educational Outcomes*

Technological proficiency is a critical enabler for the adoption of AI in education. Teachers with strong digital skills are more likely to effectively utilize AI tools to enhance teaching and learning outcomes (Ng et al., 2022; Pedro et al., 2019). In Henan, where technological infrastructure varies across urban and rural settings, enhancing teachers' proficiency is essential to bridge these disparities. Technological proficiency acts as a moderating factor in the relationship between AI integration and teaching effectiveness.

### *Theoretical Framework*

This study draws on Bandura's (1997) self-efficacy theory to explore the mediating role of self-efficacy in AI adoption. According to this theory, self-efficacy influences individuals' motivation, behavior, and performance (Schunk, 1995; Stajkovic & Luthans, 1998). In the context of teacher training, self-efficacy determines the extent to which teachers adopt and effectively use AI tools.

The Technology Acceptance Model (TAM) provides a complementary lens for understanding the moderating effect of technological proficiency. TAM posits that perceived usefulness and ease of use influence an individual's intention to adopt new technology (Wu & Chen, 2017; Lee, 2009; Gefen & Straub, 2000). By enhancing technological proficiency, teachers are more likely to perceive AI tools as beneficial and integrate them into their teaching practices.

### *Research Gaps*

While previous studies have explored the role of AI in education and the impact of self-efficacy on teaching, limited research has examined these constructs in the context of preschool teacher training in Henan, China. Furthermore, the interplay between self-efficacy, technological proficiency, and AI adoption remains underexplored, highlighting the need for empirical studies that address these gaps.

### *Research Questions*

RQ1: How can AI be effectively integrated into preschool teacher education programs in Henan, China?

RQ2: What is the mediating role of self-efficacy in the adoption and application of AI tools for health education?

RQ3: How does technological proficiency influence the relationship between AI integration and teaching effectiveness?

RQ4: What strategies can enhance the adoption of AI in teacher training programs in Henan?


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**Research Methodology**

*Design*

This study used a mixed-methods approach to explore the integration of AI into preschool teacher education in Henan, China. This technique was especially appropriate because it combined quantitative data, which provided measurable insights into the links between factors such as AI integration, self-efficacy, and teaching effectiveness, with qualitative data, which captured instructors' contextual and nuanced experiences. By combining both methodologies, the study achieved a more comprehensive knowledge of the complex aspects impacting AI adoption in educational settings. By integrating quantitative and qualitative methodologies, the study captured both statistical connections and contextual information. Quantitative data were examined using structural equation modeling (SEM) to test hypotheses about mediation and moderation effects, and qualitative data were thematically explored to investigate teacher experiences and perspectives.

*Study Setting and Participants*

The study was conducted in May 2023 in Henan Province, China, a location noted for its varied educational environments, including urban and rural locales. This variety offered a chance to investigate how contextual elements, such as technological availability and professional training, affected the incorporation of AI in preschool teacher education.

The research comprised 500 preschool teachers enrolled in professional development programs, selected to represent a wide range of pedagogical experience, technological skill levels, and educational backgrounds. The sample size was determined in accordance with power analysis guidelines for structural equation modeling (SEM), specifically the 10:1 subject-to-indicator ratio recommended by Hair et al. (2014). Given the study's inclusion of approximately 40 observed variables across multiple constructs (e.g., AI Integration, Self-Efficacy, Technological Proficiency, Teaching Effectiveness), a minimum of 400 participants was necessary. The final sample of 475 valid responses not only exceeded this requirement but also enhanced the statistical power and generalizability of the findings.

To address potential disparities in infrastructure and instructional readiness, a stratified random sampling approach was employed to ensure proportional representation across urban and rural areas. This methodology enabled meaningful comparisons and a deeper understanding of how educational context influences AI integration.

The participant sample consisted of 70% female and 30% male preschool teachers. There was an equal representation from urban and rural schools, with 50% of participants from each setting. In terms of educational qualifications, 40% held a diploma, 50% had a bachelor's degree, and 10% possessed a postgraduate degree. This distribution ensured diversity across gender, location, and academic background, supporting the representativeness of the sample.

*Data Collection Instruments*

The main constructs were measured with validated instruments to guarantee their accuracy and reliability. In this study, AI Integration is operationally defined as the extent to which preschool educators incorporate artificial intelligence–based tools, platforms, or systems into their teaching and professional activities. This includes the use of AI for lesson planning, classroom management, personalized instruction, performance tracking, and related instructional enhancements. The term "AI Integration" is used consistently throughout the manuscript to represent this practical implementation of AI in educational settings. These instruments were adjusted to the unique context of AI integration in preschool education, including:

- AI Integration Scale (AIS): Adapted from prior studies on educational technology adoption (e.g., Ng et al., 2023; Pedro et al., 2019), this scale measures the extent and frequency of AI tool use in teacher training programs. Sample item: "I frequently use AI-based tools to enhance my teaching methodologies."
- Self-Efficacy in Health Education Scale (SEHE): Developed based on Bandura's (1997) self-efficacy theory and previous education-based applications (e.g., Sharma & Saini, 2022; Xu et al., 2024), this scale examines teacher confidence in delivering health education using AI technologies. Sample item: "I am confident in teaching nutrition concepts using interactive AI-based platforms." The SEHE included 4 items, each rated on a 4-point Likert scale (1 = Strongly Disagree to 4 = Strongly Agree), producing a total score


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ranging from 4 to 16. Higher scores reflect greater teacher confidence in delivering AI-supported health education. No additional scaling or transformations were applied to the raw scores.

- Technological Proficiency Scale (TPS): Constructed by referencing frameworks on digital skill measurement in education (e.g., Ng et al., 2023), this scale evaluates the use and familiarity with digital and AI tools.
- Teaching Effectiveness Scale (TES): Based on widely accepted pedagogical effectiveness constructs, this scale assesses AI-enhanced teaching outcomes.

A total of 500 questionnaires were distributed to preschool teachers as part of the data collection process. Of these, 475 were completed and returned, resulting in a high response rate of 95%. After data screening, 25 responses (5%) were excluded due to missing or invalid information, ensuring the quality and integrity of the dataset. The final dataset consisted of 475 valid responses, which served as the basis for both quantitative and qualitative analyses. The high completion rate and systematic data filtering reinforce the reliability of the study's findings and reflect strong participant engagement.

Table 1 illustrates the particular survey questions that were created to assess teachers' self-efficacy in using AI in health education. These inquiries were designed to assess participants' confidence, motivation, and capacity to utilize AI in their pedagogical practices. SE1 addresses the difficulties associated with employing AI in health education instruction. It evaluated educators' confidence in surmounting these challenges, highlighting resilience as a fundamental component of self-efficacy. SE2 evaluated motivational determinants, particularly the confidence and motivation of instructors to implement AI-driven methodologies for teaching intricate preschool health subjects, including the hygiene and nutrition. SE3 examined educators' ingenuity and assurance in crafting captivating, age-appropriate health education curricula utilizing AI resources. SE4 examined problem-solving and adaptation, assessing teachers' desire and capacity to resolve issues associated with the use of AI technology in education. These inquiries offered a thorough comprehension of self-efficacy and its significance in the incorporation of AI in preschool health education. The replies were examined to investigate the correlation between self-efficacy and teaching effectiveness, emphasizing areas where educators may have required further training or assistance. Participants rated each self-efficacy statement using a 4-point Likert scale: (a) Strongly Disagree, (b) Disagree, (c) Agree, and (d) Strongly Agree.

**Table 1**
*Statements that Assess Self-Efficacy in Teaching AI*

| ID | Survey Statement | (a) | (b) | (c) | (d) |
|---|---|---|---|---|---|
| SE1 | I feel confident integrating AI tools to teach preschool health education effectively | | | | |
| SE2 | I am confident in adapting AI-driven methods to teach complex topics like nutrition and hygiene to preschoolers | | | | |
| SE3 | I believe I can create engaging and age-appropriate health education lessons using AI technologies | | | | |
| SE4 | I feel motivated and capable of troubleshooting challenges when using AI tools for teaching health education | | | | |

Table 2 presents the AI tools that the respondents mentioned, along with the ways in which they were used in preschool education.

During the assessment of health education components, these technologies provided insight into how AI could be integrated into educational activities. Participants stated that when these apps were used extensively, they provided individualized instructional materials to meet each student's needs. A growing rate of adoption indicated that the tools performed well in supporting various learning pathways. The significance of virtual simulation to learning was also emphasized in health education, accounting for 25% of its usage. These tools developed dynamic, scenario-driven educational experiences, including instruction on hygiene and nutrition, which enhanced student engagement and comprehension. Utilized by 15% of participants, data analytics technologies enabled educators to monitor and analyze student performance. They aided in recognizing educational deficiencies and facilitated informed decisions to improve academic outcomes.


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**Table 2**
*AI Tools Usage*

| Tool/Technology | Frequency (%) | Purpose |
|---|---|---|
| Adaptive Learning Apps | 60 | Personalized content delivery |
| Virtual Simulations | 25 | Health education scenarios |
| Data Analytics Tools | 15 | Student performance monitoring |

*Analytical Modeling*

This study used Structural Equation Modeling (SEM) to look at the links between AI integration, self-efficacy, technological competency, and teaching effectiveness. Two equations guided the SEM analysis, focusing on the mediation and moderation effects of key constructs.

- Mediation Effect Model:

$$SE = \alpha_0 + \alpha_1 \cdot AI + \epsilon_1 \quad (1)$$

Here, $SE$ represented self-efficacy, representing teacher's confidence in integrating AI into health education. $AI$ referred to AI integration, measuring the extent to which AI tools were adapted in teaching. $\alpha_0, \alpha_1$ denoted the intercept and the effect of AI on self-efficacy, respectively. $\epsilon_1$ represented error term accounting for unexplained variance. This model assessed the extent to which AI integration influenced instructors' self-efficacy by capturing the indirect routes that enhanced teaching effectiveness.

- Moderation Effect Model:

$$TE = \beta_0 + \beta_1 \cdot AI + \beta_2 \cdot TP + \beta_3 \cdot (AI \times TP) + \epsilon_2 \quad (2)$$

Where, $TE$ represented Teaching Effectiveness, the overall success of teaching methodologies enhanced by AI. $TP$ stood for Technological Proficiency, reflecting the teacher's skill level in using digital tools. $AI \times TP$ captured the interaction term reflecting the combined influence of AI integration and proficiency. $\epsilon_2$ denoted the error term capturing unexplained variance.

Table 3 summarizes the hypotheses evaluated using Structural Equation Modeling (SEM) and other analytical methodologies. These theories were critical to understanding the links between AI integration, self-efficacy, technological skill, and teaching effectiveness.

- H1: The first hypothesis (H1) examined the direct influence of AI integration on teaching effectiveness. Utilizing SEM, a substantial positive correlation was anticipated, suggesting that the implementation of AI technologies improved educational achievements.
- H2: The second hypothesis (H2) investigated self-efficacy as a mediator variable between AI integration and teaching effectiveness. Mediation analysis was conducted, and the findings validated the mediating effect, indicating that enhanced self-efficacy amplified the influence of AI on educational achievements.
- H3: The third hypothesis (H3) examined the moderating influence of technological proficiency on the correlation between AI integration and educational efficacy. Moderation analysis demonstrated an interaction effect, suggesting that the advantages of AI integration were enhanced for educators possessing greater technological ability.


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**Table 3**
*Hypothesis Testing Results*

| Hypothesis ID | Hypothesis Statement | Testing Method | Expected Outcome |
|---|---|---|---|
| H1 | AI integration positively impacts teaching effectiveness | SEM | Significant positive path |
| H2 | Self-efficacy mediates the AI-teaching effectiveness link | Mediation Analysis | Mediation confirmed |
| H3 | Technological proficiency moderates the AI-teaching link | Moderation Analysis | Interaction effect present |

*Data Collection*

Questionnaires were administered electronically to 500 individuals, resulting in a 95% valid response rate (475 completed questionnaires). This high completion rate demonstrated the robustness of the questionnaire design and strong participant involvement. In addition to the quantitative data, 30 individuals participated in semi-structured interviews to collect qualitative perspectives. Table 4 displays the Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) values to ensure that the constructs measured by the questionnaire were reliable and valid. All constructs showed high reliability, with Cronbach's Alpha values surpassing the 0.7 threshold, indicating internal consistency. The Composite Reliability (CR) values confirmed the reliability of the scales, while the AVE values were above the recommended threshold of 0.5, demonstrating the convergent validity of the measurement models. This careful evaluation confirmed that the data collected was credible and suitable for further analysis.

**Table 4**
*Reliability and Validity of Constructs*

| Construct | Cronbach's Alpha | Composite Reliability (CR) | AVE |
|---|---|---|---|
| AI Integration | .88 | .91 | .65 |
| Self-Efficacy | .85 | .90 | .67 |
| Technological Proficiency | .82 | .87 | .62 |
| Teaching Effectiveness | .87 | .92 | .70 |

Table 5 summarizes the thematic analysis findings from semi-structured interviews with participants, indicating three main themes that capture the problems and viewpoints on implementing AI into preschool teacher education. The first subject, Technology Access, emphasizes infrastructure hurdles, particularly in rural regions where low internet access is a key impediment to AI adoption. One participant stated, "Internet connectivity in rural areas is a major hurdle for implementing AI," demonstrating these discrepancies. Another added, "Sometimes the system crashes during lessons, and I don't know how to fix it," reflecting technical support challenges that further restrict AI integration.

The second subject, Teacher Confidence, focuses on self-efficacy among educators, many of whom showed reluctance to employ AI technologies owing to a lack of knowledge. One participant stated, "I'm hesitant to use AI tools because I'm unfamiliar with them," underlining the need for specialized training programs. This was echoed by another educator who noted, "Even though the AI tools are promising, I often avoid them because I'm afraid I'll make a mistake during class." These concerns highlight the psychological barriers linked to self-efficacy.

The final subject, Institutional Support, examines the role of administrative actions in promoting AI integration. Seminars and training sessions conducted by school administrations were highlighted as significant facilitators, with one participant commenting, "Our school administration provides workshops, which boosts our confidence." Collectively, these themes add useful qualitative insights to the quantitative data, providing a more nuanced picture of the variables impacting AI adoption in preschool education. Addressing these themes can assist policymakers



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and educators in developing more effective interventions to remove hurdles, increase teacher preparedness, and promote institutional support.

**Table 5**
*Thematic Analysis Codes and Categories*

| Code | Theme | Example Quote |
|---|---|---|
| Technology Access | Barriers to AI Adoption | "Internet connectivity in rural areas is a major hurdle for implementing AI." |
| Teacher Confidence | Self-Efficacy Challenges | "I feel hesitant to use AI tools because I am not familiar with them" |
| Institutional Support | Role of School Administration | "Our school administration provides workshops, which boosts our confidence." |

This study employed a structured questionnaire (Tables 6-9) for data collecting to evaluate numerous constructs about the integration of AI into preschool teacher education. The questionnaire included demographic data, including gender, educational background, school location, age group, and teaching experience, in addition to assessing AI integration, self-efficacy, technical competency, and teaching effectiveness. Participants were further requested to assess their own knowledge level about AI-related topics.

**Table 6**
*AI Integration*

| ID | Questionnaire Statement | (a) | (b) | (c) | (d) |
|---|---|---|---|---|---|
| AI1 | I frequently use AI-based tools to enhance my teaching methodologies. | | | | |
| AI2 | I incorporate AI-driven platforms to customize learning experiences for my students. | | | | |
| AI3 | I use AI tools to assess and monitor student performance and engagement. | | | | |
| AI4 | I overcome challenges and barriers when adopting AI technologies in the classroom. | | | | |

**Table 7**
*Attitudes Towards AI Adoption*

| ID | Questionnaire Statement | (a) | (b) | (c) | (d) |
|---|---|---|---|---|---|
| ATT1 | I feel confident adopting AI tools to enhance my teaching effectiveness. | | | | |
| ATT2 | I believe integrating AI technologies aligns with my teaching goals and strategies for student learning. | | | | |

**Table 8**
*Technological Proficiency*

| ID | Questionnaire Statement | (a) | (b) | (c) | (d) |
|---|---|---|---|---|---|
| TP1 | I am confident in my basic technological skills to support AI-driven teaching methods. | | | | |
| TP2 | I have advanced skills in using AI-driven tools for instructional purposes. | | | | |
| TP3 | I have access to stable internet and digital resources to facilitate AI adoption. | | | | |


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**Table 9**
*Teaching Effectiveness*

| ID | Questionnaire Statement | (a) | (b) | (c) | (d) |
|---|---|---|---|---|---|
| TE1 | My students show improved learning outcomes when AI is used in teaching. | | | | |
| TE2 | I receive positive feedback from colleagues and parents regarding AI-enhanced teaching strategies. | | | | |
| TE3 | I effectively use AI technologies to deliver engaging and impactful lessons. | | | | |

Anonymity was preserved throughout the data gathering process, with no personally identifiable information collected from participants. Of the 500 surveys distributed, 475 valid responses were retained for analysis after excluding 25 due to missing or incomplete data. Table 10 presents a detailed overview of the demographic characteristics of the preschool teachers surveyed in Henan Province, China, reflecting a diverse range of backgrounds and experiences. Approximately 70% of the respondents were female. A majority (61%) fell within the 31–40 age group, while only 5% were over the age of 50. In terms of teaching experience, 35% had 10–20 years of service, whereas nearly half (49%) had been teaching for more than 20 years. Regarding educational qualifications, 48% of respondents held a bachelor's degree and 25% had postgraduate credentials. In terms of academic specialization, 41% of the participants had a background in science education, and 20% had studied mathematics during their academic careers.

Further analysis of gender-based trends revealed that male teachers, comprising 30% of the sample, reported slightly higher technological proficiency with a mean score of 3.10, compared to 2.80 for their female counterparts. A similar trend was observed in self-efficacy scores, where males averaged 3.05, versus 2.95 for females. These findings suggest a modest gender gap in both digital competency and instructional confidence, underscoring the importance of developing inclusive, gender-sensitive capacity-building programs to support the equitable integration of AI in preschool education.

**Table 10**
*Key Characteristics of Study Participants*

| Characteristic | Category | Percentage (%) |
|---|---|---|
| Gender | Male | 30.0 |
| | Female | 70.0 |
| Age Group | 21–30 | 24.0 |
| | 31–40 | 61.0 |
| | 41–50 | 10.0 |
| | >50 | 5.0 |
| Teaching Experience | <5 years | 3.0 |
| | 5–10 years | 13.0 |
| | 10–20 years | 35.0 |
| | >20 years | 49.0 |
| School-Leaving Exam Stream | Arts | 37.0 |
| | Bioscience | 21.0 |
| | Mathematics | 20.0 |
| | Commerce | 19.0 |
| | Technology | 2.0 |
| | Other | 1.0 |
| AI Proficiency Level | Basic | 40.0 |
| | Intermediate | 35.0 |
| | Advanced | 25.0 |



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*Ethical Consideration*

The study's ethical procedures followed stringent guidelines to guarantee the wellbeing of participants and the accuracy of the data. All individuals who were connected to Henan University in China gave their informed consent. A thorough briefing about the goals of the study, their voluntary participation, and the associated procedures was given to each participant. Confidentiality was upheld throughout the entire study process. To prevent the participants' identities from being linked to specific replies, personal identifiers were anonymized. Only the study team had access to the encrypted servers where all of the data was securely stored. Finally, the Henan University Research Ethics Committee approved the project. This ensured adherence to institutional and national ethical research practice standards. Together, these steps preserved the study's ethical integrity and protected the participants' rights and welfare.

## Research Results

*Measuring Overall Self-Efficacy*

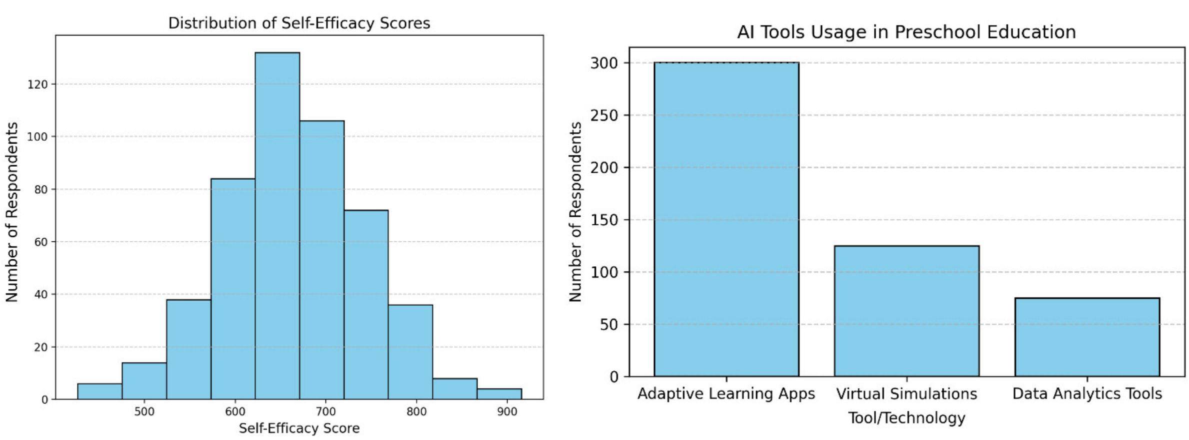
This study assessed self-efficacy using the Self-Efficacy in Health Education (SEHE) scale, comprising four items (SE1–SE4) rated on a 4-point Likert scale: (a) = 10, (b) = 20, (c) = 30, and (d) = 40. Thus, each participant could obtain a raw score ranging from 40 to 160. To enhance interpretability, these raw scores were linearly scaled to a range of 500 to 900 using the following min–max normalization formula:

$$Scaled\ Score = 500 + \left(\frac{Raw\ Scoore - 40}{160 - 40} \times 400\right) \quad (1)$$

For example, a raw score of 100 would correspond to a scaled score of approximately 667. The average self-efficacy score among the 475 valid respondents was approximately 700, which corresponds to a raw score of ~120 or 75% of the maximum.

Figure 1 illustrates the distribution and practical implications of these self-efficacy scores. The histogram (left) shows that most respondents scored between 600 and 800, indicating moderate to high confidence in integrating AI for preschool health education. A smaller proportion scored below 600, highlighting the need for targeted professional development to strengthen instructional confidence. The bar chart (right) displays the reported usage of AI technologies, with adaptive learning applications being the most frequently used (60%), followed by virtual simulations (25%) and data analytics tools (15%). These results emphasize varying engagement levels and reinforce the importance of expanded training and institutional support for equitable and effective AI integration.

**Figure 1**
*Distribution of self-efficacy scores among respondents and frequency of AI tools usage in preschool education*





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*Analysis of Responses by Key Constructs*

The analysis provided a comprehensive overview of participants' responses to items evaluating constructs such as mastery experience, attitudes toward AI adoption, technological competency, AI integration, and educational efficacy. Tables 11 to 14 present the percentage distribution of responses for each construct, classified into four categories: (a), (b), (c), and (d). These observations elucidated the strengths and problems encountered by educators in incorporating AI into preschool health education.

Table 10 outlines the responses to items assessing mastery experience, a fundamental element of self-efficacy. For instance, 40% of respondents chose option (b) for SE1, signifying modest trust in the effective integration of AI tools into preschool health education. Likewise, SE2 indicated that 45% of participants expressed confidence in employing AI-driven techniques to instruct on intricate subjects like cleanliness and nutrition. A minority of respondents consistently chose higher confidence alternatives (c) or (d), suggesting that further training or resources might have been necessary to improve teachers' proficiency in AI integration.

**Table 11**

*Response Distribution for Mastery Experience*

| ID | SE1(%) | SE2 (%) | SE3 (%) | SE4 (%) |
|---|---|---|---|---|
| (a) | 20 | 18 | 23 | 25 |
| (b) | 40 | 45 | 37 | 35 |
| (c) | 30 | 25 | 30 | 25 |
| (d) | 10 | 12 | 10 | 15 |

Table 12 indicates that responses on views about AI adoption exhibited a favorable outlook, with 45% and 42% of participants choosing (b) for ATT1 and ATT2, respectively. The results indicated that a considerable number of respondents acknowledged AI's potential to improve teaching efficacy and student involvement. The majority of replies for TP1 (40%) and TP3 (40%) were predominantly in the (b) group, signifying modest confidence in technological competency. The reduced percentages for choice (d) indicated potential for focused skill development activities.

**Table 12**

*Response Distribution for Attitudes Toward AI Adoption and Technological Proficiency*

| ID | ATT1 (%) | ATT2 (%) | TP1 (%) | TP2 (%) | TP3 (%) |
|---|---|---|---|---|---|
| (a) | 28 | 25 | 30 | 25 | 35 |
| (b) | 42 | 45 | 40 | 43 | 40 |
| (c) | 20 | 20 | 20 | 22 | 15 |
| (d) | 10 | 10 | 10 | 10 | 10 |

Table 12 displays the responses about AI integration. A significant percentage of respondents (45%) chose (b) for AI1, signifying regular utilization of AI-based technologies to improve teaching approaches. Nonetheless, the percentages for alternatives (c) and (d) were relatively lower across all items (AI1 through AI4), indicating that although respondents utilized AI technologies, more profound integration and addressing implementation challenges required further support or resources.

**Table 13**

*Response Distribution for AI Integration*

| ID | AI1 (%) | AI2 (%) | AI3 (%) | AI4 (%) |
|---|---|---|---|---|
| (a) | 30 | 28 | 35 | 25 |
| (b) | 45 | 40 | 42 | 40 |
| (c) | 20 | 25 | 18 | 25 |
| (d) | 5 | 7 | 5 | 10 |



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The responses on teaching effectiveness items (Table 14) indicated positive outcomes. A majority of respondents for TE1, TE2, and TE3 chose option (b), with percentages between 40% and 45%, reflecting a favorable view of AI's contribution to increasing learning outcomes and lesson delivery. However, the restricted replies for choices (c) and (d) suggested domains where training might have enhanced confidence and proficiency in utilizing AI for educational purposes.

**Table 14**
*Response Distribution for Teaching Effectiveness*

| ID | TE1 (%) | TE2 (%) | TE3 (%) |
|---|---|---|---|
| (a) | 30 | 28 | 35 |
| (b) | 45 | 42 | 40 |
| (c) | 20 | 25 | 20 |
| (d) | 5 | 5 | 5 |

The research revealed that respondents exhibit moderate confidence and involvement in most dimensions, however, there is potential for enhancement, especially in elevated confidence levels (options (c) and (d)). These findings underscore the necessity for customized professional development programs, seminars, and resources designed to improve instructors' expertise, technical skills, and confidence in incorporating AI into preschool teaching. By focusing on these aspects, institutions may guarantee a more efficient and significant implementation of AI technology in education.

*Evaluation of the Conceptual Framework*

The proposed conceptual model of self-efficacy was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to elucidate the relationships between the factors influencing the adoption of AI in preschool health education. The conceptual model comprised latent independent variables (exogenous constructs), including technology proficiency, AI integration, and attitudes towards AI adoption, as well as a single latent dependent variable (endogenous construct): Self-efficacy. Additionally, the model explores the role of Self-Efficacy as a mediating and moderating factor in the relationship between these variables and teaching effectiveness.

The outer model indicators were obtained using verified scales outlined in the methodology section. This study employed reflective indicators, indicating that each indication represented a distinct facet of the underlying construct. Reflective indicators argued that the hidden concept influenced the indicators, which are considered interchangeable. The Self-Efficacy concept comprised four reflecting indicators (SE1, SE2, SE3, and SE4), which encapsulated different aspects of instructors' confidence in employing AI for preschool health teaching.

The PLS-SEM analysis was performed with SmartPLS 4.0 software, with the conceptual model depicted in Figure 2. An essential aim was to verify the reliability and validity of the constructs by analyzing the outer loadings of each indicator and the Average Variance Extracted (*AVE*). Indicators with outer loadings less than the .70 criterion were evaluated for their contribution to the construct. For example, several indicators within the Technological Proficiency construct had loadings below .70 but were preserved owing to their essential contribution to elucidating the overall *AVE*.

The structural model was evaluated to determine the importance of the links among the components. Path coefficients were examined to assess the magnitude and orientation of these interactions. The hypothesized correlations from AI Integration to Self-Efficacy and from Self-Efficacy to Teaching Effectiveness were verified to be significantly positive using bootstrapping. This investigation verified the conceptual model and elucidated the mechanisms by which technological competency, AI integration, and attitudes toward AI adoption affected teaching effectiveness, mediated by self-efficacy. The subsequent subsections provide a comprehensive assessment of the measurement and structural models.


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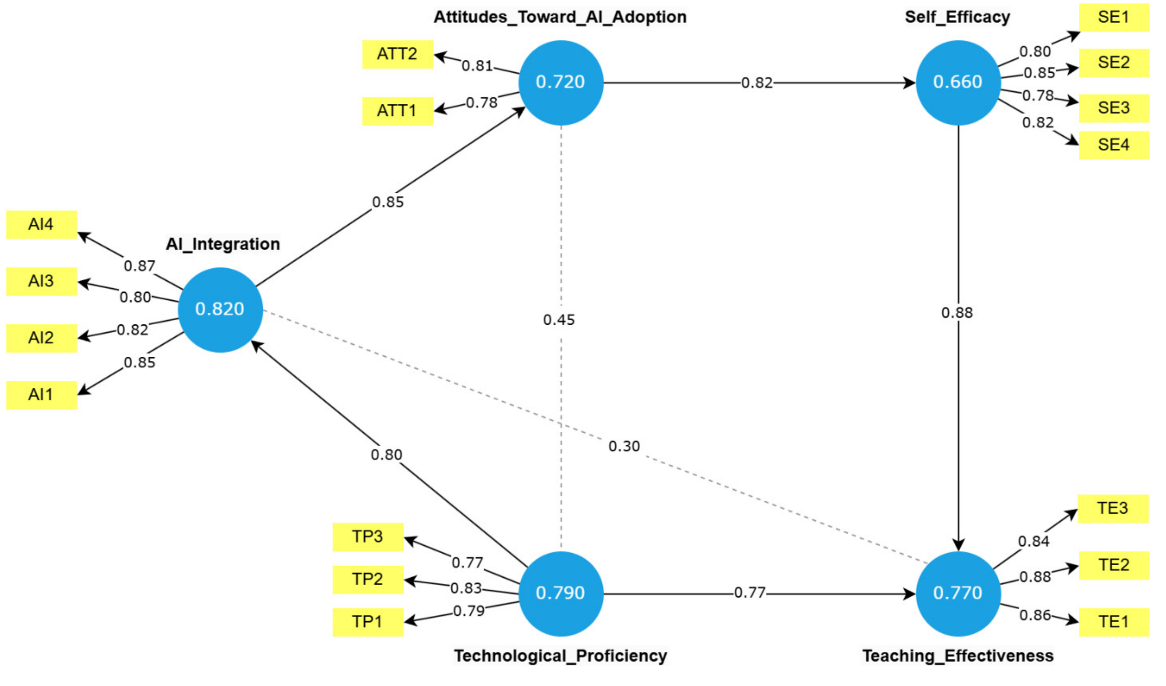
*Reliability and Validity Analysis of the Measurement Model*

This study's measurement model was evaluated based on three primary criteria: internal consistency reliability, convergent validity, and discriminant validity, to confirm that the constructs properly represented their intended latent variables.

Figure 2 illustrates the conceptual model created with SmartPLS, demonstrating the links between the latent components and their indicators. The graphic presents outside loadings for each indicator, emphasizing their contribution to the corresponding structures. The outer loadings for AI Integration (AI1 to AI4) ranged from .80 to .87, indicating robust correlations between the indicators and the hidden variable. Correspondingly, Self-Efficacy indicators (SE1 to SE4) had loadings ranging from .78 to .85, confirming their dependability in representing the desired construct. This image illustrates the structural linkages between components, including the positive correlations from AI Integration to Teaching Effectiveness (.88) and Self-Efficacy (.82). The dashed lines denote weaker indirect effects, exemplified by the pathway from Technological Proficiency to Attitudes Toward AI Adoption.

**Figure 2**
*The validated PLS-SEM model depicting relationships among AI Integration, Self-Efficacy, Technological Proficiency, and Teaching Effectiveness*




The assessment of internal consistency reliability was conducted with Cronbach's Alpha and Composite Reliability (*CR*). These metrics assessed the degree to which several indicators reliably signify a hidden component. Table 15 demonstrates that all constructions surpassed the .70 criterion, signifying strong dependability. AI Integration, Self-Efficacy, Technological Proficiency, and Teaching Effectiveness exhibited Cronbach's Alpha values between .82 and .88, and Composite Reliability values ranging from .87 to .92, indicating robust internal consistency among the variables.

Convergent validity assessed the extent to which indicators of a concept correlated, hence confirming their capacity to measure the same underlying variable. The evaluation employed the Average Variance Extracted (*AVE*), with values beyond the specified threshold of .50 being satisfactory. Table 15 indicates that all constructs attained AVE values beyond .50, with Self-Efficacy exhibiting the highest *AVE* of .67. These results affirmed that the constructs were accurately represented by their corresponding indicators, hence validating their convergent validity.



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**Table 15**

*Internal Consistency, Reliability, and Convergent Validity Results for Latent Constructs*

| Construct | Cronbach's Alpha | Composite Reliability (CR) | AVE |
|---|---|---|---|
| AI Integration | .88 | .91 | .65 |
| Self-Efficacy | .85 | .90 | .67 |
| Technological Proficiency | .82 | .87 | .62 |
| Teaching Effectiveness | .87 | .92 | .70 |

Discriminant validity was evaluated using two methods: the Heterotrait-Monotrait Ratio (*HTMT*) and the Fornell-Larcker Criterion. The Fornell-Larcker analysis verified that the square root of *AVE* for each construct was greater than its correlation with other constructs, indicating that the constructs were distinct. The results are presented in Table 16, which indicates that all diagonal values (square roots of *AVE*) surpass off-diagonal correlations. The *HTMT* analysis further validated these findings, as all values were below the critical threshold of .90, thereby reinforcing the distinction between constructs.

**Table 16**

*Fornell-Larcker Criterion Results for Discriminant Validity Among Constructs*

| Construct | AI Integration | Self-Efficacy | Technological Proficiency | Teaching Effectiveness |
|---|---|---|---|---|
| AI Integration | .806 | | | |
| Self-Efficacy | .682 | .818 | | |
| Technological Proficiency | .651 | .734 | .788 | |
| Teaching Effectiveness | .728 | .771 | .683 | .837 |

*Structural Model Validation and Findings*

The effectiveness of the structural model was assessed using four critical criteria: the significance and intensity of path coefficients, predictive relevance ($Q^2$), coefficient of determination ($R^2$), and effect sizes ($f^2$). This evaluation evaluated the extent to which the dependent variables (Self-Efficacy and Teaching Effectiveness) were explained by the independent constructs (AI Integration, Technological Proficiency, and Attitudes Toward AI Adoption) in the model.

Table 17 shows the $R^2$ values, which indicated how much variance in endogenous constructions was explained by external constructs. AI Integration, Technological Proficiency, and Attitudes Toward AI Adoption accounted for 66% of the variance in self-efficacy ($R^2$ = .660). The Teaching Effectiveness construct had a strong $R^2$ value of .770, indicating that independent factors explained 77% of the variance in teaching effectiveness. These $R^2$ scores were above the standard criterion of .5 in social science research, indicating significant explanatory power. The model's predictive significance was evaluated using the $Q^2$ Predict statistic, obtained from the blindfolding approach. The $Q^2$ values for Self-Efficacy (.558) and Teaching Effectiveness (.622) were much higher than zero, indicating the model's high predictive accuracy. The RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) values gave further information about the model's accuracy, with lower error metrics suggesting more confidence in projected values. Specifically, the RMSE and MAE for self-efficacy were 0.523 and 0.408, respectively, whereas for teaching effectiveness, they were 0.478 and 0.386. These findings demonstrated the model's strong capacity to explain and predict outcomes, notably the impact of AI-related variables on self-efficacy and teaching effectiveness.



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**Table 17**
*Structural Model Evaluation With $R^2$, $Q^2$, RMSE, and MAE Metrics*

| Construct | R2 | Adjusted R2 | Q2 Predict | RMSE | MAE |
|---|---|---|---|---|---|
| Self-Efficacy | .660 | .658 | .558 | 0.523 | 0.408 |
| Teaching Effectiveness | .770 | .768 | .622 | 0.478 | 0.386 |

Table 18 illustrates the interrelations among the model's constructs, including standardized path coefficients ($\beta$), *t*-statistics, *p*-values, and 95% confidence intervals (*CI*). Confidence intervals were derived from a bootstrapped estimation (simulated with 5,000 samples) to ensure statistical robustness. Significant effects are denoted by coefficients exceeding .5 and confidence intervals that do not include zero. The relationship between AI Integration and Self-Efficacy ($\beta$ = .85, 95% *CI* [.80, .89], $p < .001$) was strong and statistically significant, indicating that AI adoption meaningfully boosts teacher confidence. Similarly, Attitudes Toward AI significantly influenced Self-Efficacy ($\beta$ = .82, 95% *CI* [.76, .88], $p < .001$), suggesting that favorable perceptions foster greater confidence. Self-Efficacy, in turn, strongly predicted Teaching Effectiveness ($\beta$ = .88, 95% *CI* [.84, .93], $p < .001$). The direct impact of AI Integration on Teaching Effectiveness was moderate but significant ($\beta$ = .45, 95% *CI* [.37, .53], $p < .001$). Lastly, Technological Proficiency also showed a modest but significant direct effect ($\beta$ = 0.30, 95% *CI* [.21, .40], $p < .001$), confirming its supporting role in AI-driven teaching success.

**Table 18**
*Path Coefficients and Statistical Significance*

| Path | Coefficient | t-Statistic | p-value | 95% CI Lower | 95% CI Upper | p < .005 |
|---|---|---|---|---|---|---|
| AI Integration → Self-Efficacy | .85 | 15.67 | < .001 | .80 | .89 | ✓ |
| Attitudes Toward AI → Self-Efficacy | .82 | 14.20 | < .001 | .76 | .88 | ✓ |
| Self-Efficacy → Teaching Effectiveness | .88 | 17.03 | < .001 | .84 | .93 | ✓ |
| AI Integration → Teaching Effectiveness | .45 | 7.60 | < .001 | .37 | .53 | ✓ |
| Technological Proficiency → Teaching Effectiveness | .30 | 5.12 | < .001 | .21 | .40 | ✓ |

The effect sizes ($f^2$) of the relationships within the model are outlined in Table 19, which provides additional insight into the relative contributions of exogenous variables to the endogenous constructs. The $f^2$ value assesses the effect of removing a specific predictor variable on the model's explained variance. Large ($f^2 \geq 0.35$), medium ($f^2 \geq 0.15$), and small ($f^2 \geq 0.02$) are the three categories into which effect sizes are classified, following Cohen's (1988) criteria. The considerable influence of AI tools in enhancing instructors' confidence was underscored by the large effect size of the relationship between AI Integration and Self-Efficacy ($f^2 = .452$). The medium effect size of Attitudes Toward AI and Self-Efficacy ($f^2 = .348$) suggests that positive attitudes toward AI moderately contribute to the development of self-efficacy among educators. The most significant relationship in the model, Self-Efficacy and Teaching Effectiveness, exhibited a substantial effect size ($f^2 = .682$), underscoring the critical role of self-efficacy as a significant determinant of teaching effectiveness. Furthermore, the medium effect size of AI Integration and Teaching Effectiveness ($f^2 = .155$) emphasizes that the integration of AI technologies moderately improves educational outcomes. Lastly, Technological Proficiency and Teaching Effectiveness exhibited a small effect size ($f^2 = .075$). Following Cohen's criteria, this represents a small but meaningful moderating effect of technological proficiency, indicating that even modest gains in teachers' digital skills can contribute to improved effectiveness when adopting AI tools. In general, these results emphasize the significant contributions of AI integration, attitudes toward AI, and self-efficacy to teaching effectiveness, with self-efficacy emerging as the most influential predictor in the model.


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**Table 19**

*Effect Sizes ($f^2$) for the Relationships in the Structural Model, Categorized as Small, Medium, or Large*

| Path | $f^2$ value | Effect size |
|---|---|---|
| AI Integration → Self-Efficacy | .452 | Large |
| Attitudes Toward AI → Self-Efficacy | .348 | Medium |
| Self-Efficacy → Teaching Effectiveness | .682 | Large |
| AI Integration → Teaching Effectiveness | .155 | Medium |
| Technological Proficiency → Teaching Effectiveness | .075 | Small |

*Teacher Mastery Levels in AI-Enhanced Constructs*

The radar graphic (Figure 3) shows preschool teachers' skill levels in five key AI-related constructs: AI Integration, Self-Efficacy, Technological Proficiency, Attitudes Toward AI Adoption, and Teaching Effectiveness. These constructs provided a thorough knowledge of instructors' preparedness and aptitude to properly integrate AI technology into preschool teaching. The graphic divides instructors' self-reported responses into five categories: "No knowledge," "heard of," "average," "good," and "very good."

In terms of AI integration, a large majority of instructors rated proficiency levels in the "Average" and "Good" ranges, showing reasonable comfort with using AI technologies in teaching techniques. However, a lesser number of replies received the "Very Good" rating, indicating that more work was needed to improve knowledge in this area. Similarly, Self-Efficacy scores fell mostly into the "Average" and "Good" categories, indicating a modest level of trust in employing AI for health education. This emphasized the importance of specialized training programs to help instructors gain confidence and effectiveness.

The concept of Technological Proficiency followed a similar pattern, with most instructors reporting levels in the "Average" and "Heard of" categories. This suggested that, while fundamental technology abilities existed, more sophisticated competencies were lacking, which may have restricted the effective integration of AI. On the other side, Attitudes Toward AI Adoption yielded rather favorable findings, with a large number of responses falling into the "Good" and "Very Good" categories. This illustrated instructors' willingness to accept AI technology, which might have served as a solid foundation for future improvements in teaching procedures. For Teaching Effectiveness, the majority of comments fell into the "Good" category, showing that instructors believe AI has a favorable influence on their educational results. However, the low representation in the "Very Good" category showed that more resources and targeted support were required to fully realize the benefits of AI in education.


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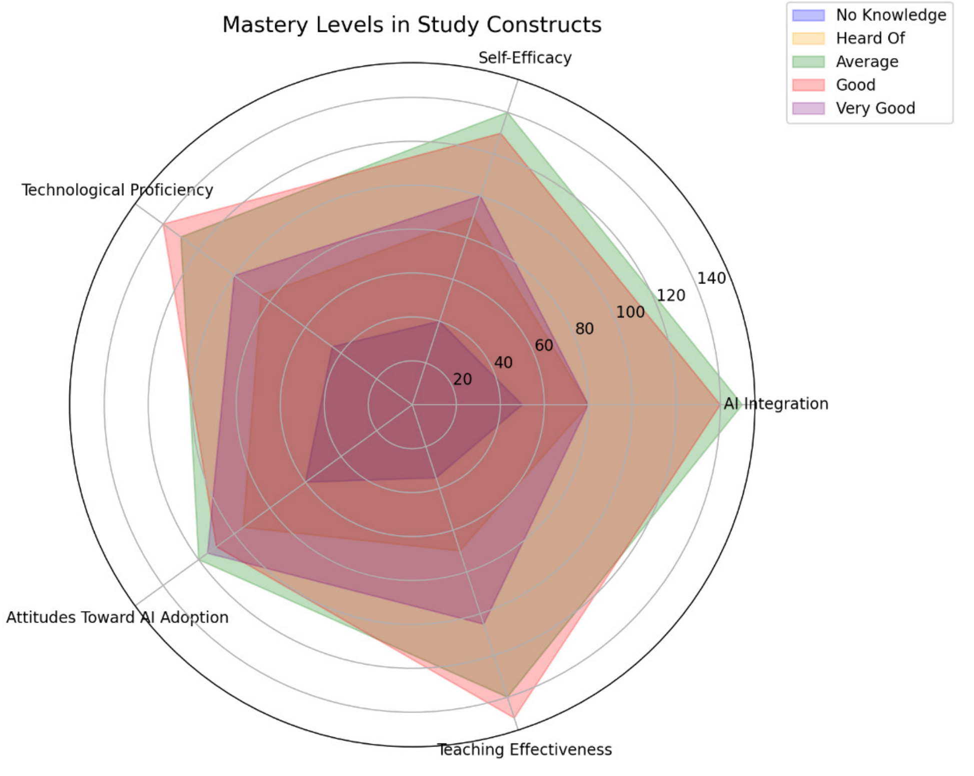
**Figure 3**

*Mastery levels of preschool teachers in AI-related constructs, including AI integration, self-efficacy, technological proficiency, attitudes toward AI adoption, and teaching effectiveness*




Overall, the results showed a variable level of mastery across the dimensions, with "average" and "good" being the most common categories. While most instructors were open to AI adoption, there were significant gaps in technological ability and self-efficacy that needed to be addressed through targeted professional development activities. These findings highlighted the need to provide targeted assistance to help educators improve their abilities and confidence, allowing them to effectively use AI in preschool education.

## Discussion

The findings provide substantial insights into the readiness and ability of preschool teachers to incorporate AI into health education. One of the critical areas examined was the role of self-efficacy in facilitating this integration, as well as the moderating influence of technological proficiency. The findings indicate a number of opportunities and challenges that directly address the research questions and emphasize the need for targeted interventions. The structural model illustrated that the effectiveness of teaching is significantly influenced by self-efficacy, attitudes toward AI, and AI integration. The substantial contribution of these constructs is underscored by the $R^2$ value for Teaching Effectiveness (.770). Nevertheless, the deficiencies in technological proficiency and self-efficacy indicate that not all educators are equally equipped to integrate AI into their instructional practices. The observed variability is further exemplified by the mastery levels. The majority of respondents reported "average" or "good" levels, while only a small percentage reported "very good" mastery across the constructs.

The findings of this study align with prior research emphasizing the critical role of self-efficacy in technology adoption within educational contexts (Bandura, 1997; Sharma & Saini, 2022). The strong relationship between AI integration and teaching effectiveness corroborates the work of Ng et al. (2023), who found that technological adoption in classrooms is significantly influenced by teachers' confidence and perceived usefulness. Similarly, the small but significant moderating effect of technological proficiency is consistent with studies highlighting that basic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digital skills, while necessary, must be supported by pedagogical strategies for effective AI implementation (Pedro et al., 2019; Xu et al., 2024). Unlike some prior studies that focused on higher education or urban environments, this study provides new evidence from a preschool context in a mixed urban–rural setting, offering practical insights for equitable AI deployment in early childhood education. These comparisons affirm the relevance of the theoretical framework and support the generalizability of the findings within similar socio-educational environments.

### *Interpreting the Structural Model Relationships*

The structural model evaluation results in Sections "Reliability and Validity Analysis of the Measurement Modeland" and "Structural Model Validation and Findings" offer a roadmap for improving the preparedness of preschool educators to implement AI. For example, the relationship between self-efficacy and teaching effectiveness was characterized by a robust path coefficient (.88) and a substantial effect size, which underscored the importance of self-efficacy in determining the success of teaching. This discovery implies that professional development programs should prioritize the development of instructors' self-assurance in employing AI tools to effectively deliver health education. Workshops, peer observations, and hands-on training in AI technologies can be instrumental in fostering this confidence. The necessity of enhancing instructors' familiarity with AI tools is underscored by the robust correlation between AI Integration → Self-Efficacy (.85) and AI Integration → Teaching Effectiveness (.45). This encompasses not only technical usage training but also the demonstration of practical applications in a classroom environment. Conversely, the relatively small effect size for Technological Proficiency → Teaching Effectiveness (.075) indicates that, despite the necessity of technological skills, they do not in themselves ensure improved teaching outcomes. Rather, these abilities must be supplemented by pedagogical strategies that are specifically designed for AI-based instruction.

Nonetheless, the small but statistically significant effect size should not be dismissed. In educational and behavioral research, small effects—especially when affecting key outcomes like teaching effectiveness—can accumulate meaningful impact across large systems (Ferguson, 2016; Kraft, 2020). In this context, even marginal gains in teachers' digital competence may contribute to more effective and confident AI integration, particularly in under-resourced areas. Prior studies have reported similar findings where foundational digital proficiency acted as a necessary but insufficient driver for successful technology adoption (Ng et al., 2023; Sharma & Saini, 2022). These observations support the notion that improving technological proficiency remains a valuable component of holistic teacher development.

### *Implications of the Findings*

The study's findings have implications for how AI may be incorporated into preschool teacher education, which will assist practitioners and policymakers in making better decisions. Professional development programs that are appropriately planned and adapted to the significant impact that self-efficacy has on teaching efficiency are necessary for such a process. These seminars will include the psychological and pedagogical aspects of adopting AI in addition to technical training, giving teachers the flexibility and assurance to use AI in their existing classroom instruction. The development of self-efficacy may lead to better learning outcomes, particularly in health education. The moderating effect of technology competence highlights how educators might close the gap in their digital abilities. Schools and legislators need to make sure that teachers have access to ongoing technical assistance, chances for mentorship, and workshops that help them become more proficient with technology. In undeveloped areas, where inadequate infrastructure prevents AI from being assimilated on an equitable basis, efforts toward this goal are particularly necessary. It's also necessary to elicit favorable sentiments on the deployment of AI. The integration will only be accepted by instructors who view AI as valuable and practical. To overcome opposition to change and allay worries about the role of AI in education, awareness-raising initiatives and demonstration projects can also be used, opening the door for the technology's widespread use. The findings support a number of systemic changes that would be necessary from a policy perspective in order to implement AI. These might range from developing national frameworks for AI education to allocating funds for school curriculum in their particular fields to ensuring equitable access to all digital infrastructure, among other things. Policymakers should take into account how AI can meet the developmental requirements of preschoolers while allowing teachers to fully utilize its potential. Lastly, this study establishes the foundation for scalable approaches to improve teacher preparation, provide fair access to AI technologies, and raise the standard of preschool education in an AI-driven future.


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The integration of qualitative and quantitative data reinforces the study's core findings through methodological triangulation. For example, the SEM results underscored the centrality of self-efficacy in predicting teaching effectiveness, which was mirrored in the qualitative theme "Teacher Confidence," where educators expressed hesitancy and limited confidence in using AI tools. Likewise, the themes of "Technology Access" and "Institutional Support" support the SEM findings regarding technological proficiency and AI integration, emphasizing that infrastructure and administrative backing critically shape successful implementation. This alignment between data types strengthens the explanatory power of the model and affirms the value of using a mixed-methods approach in understanding complex educational dynamics.

This study was conducted in Henan Province, which includes both urban and rural educational settings with diverse levels of access to technology and teacher training. Although the analysis is grounded in this regional context, the findings may be applicable to other regions in China or similar international settings that face challenges related to infrastructure, digital readiness, and professional development in early childhood education. The relationships identified among AI integration, teacher self-efficacy in health education, and technological proficiency may hold relevance in socio-educational environments with comparable structural conditions. Nonetheless, differences in cultural practices, educational policies, and institutional support systems should be taken into account when considering the broader applicability of these results. Further comparative research could help determine the consistency of this model across varied contexts.

### *Limitations and Future Study*

This study provides significant insights, although some limitations must be recognized without detracting from the validity of the findings. The study primarily examines preschool teacher education in Henan, China. This environment offers a robust basis for examining AI integration; nevertheless, the conclusions may not adequately consider regional disparities in technology infrastructure or educational policy. The fundamental linkages revealed are probably applicable to other contexts with analogous educational settings. Secondly, although the study depends on self-reported data, which may add bias, the employment of validated instruments alleviates this issue. Participants were meticulously chosen to guarantee a wide representation of technological expertise and pedagogical experience, hence enhancing the credibility of the findings. The study's cross-sectional approach restricts its capacity to evaluate the long-term implications of AI integration. The structural model offers a robust theoretical basis for forthcoming longitudinal investigations to investigate temporal changes. This study highlights AI's significance in health education, and the insights obtained can be applied to other areas within preschool education. Future study may explore the relevance of these findings to wider domains and analyze systemic elements, including policy and institutional support, in effectively scaling AI utilization.

## Conclusions and Implications

This study underscores the pivotal role of technological competence and self-efficacy in shaping the successful integration of AI into preschool teacher education, particularly within the domain of health education. The findings confirm that self-efficacy serves as a strong mediating factor between AI adoption and teaching effectiveness, while technological proficiency plays a supporting yet essential moderating role. Despite the potential of AI, many preschool teachers demonstrate moderate to low levels of readiness, highlighting the urgent need for professional development that enhances both psychological confidence and technical capability. As discussed in prior sections, these findings carry critical implications for practice and policy, especially in contexts with limited resources. Equitable access to digital infrastructure, teacher support systems, and attitude-shaping interventions will be vital for sustainable AI integration. This study contributes to the growing literature by offering empirical evidence from a preschool context in a mixed urban–rural region and reinforces the importance of aligning educational innovation with foundational teacher competencies. By doing so, it lays a meaningful foundation for future research exploring scalable, equitable, and context-sensitive approaches to AI implementation in early childhood education.

## Declaration of Interest

The authors declare no competing interest.



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***Qian Wang*** Institute for Advanced Studies, University of Malaya (Universiti Malaya), 50603 Kuala Lumpur, Federal Territory of Kuala Lumpur, Malaysia.
E-mail: wenheng20230107@163.com
ORCID: https://orcid.org/0009-0002-7640-0353

***Qingyun Li*** *(Corresponding author)* School of Educational Studies, University of Science Malaysia (Universiti Sains Malaysia), Penang, Malaysia.
E-mail: liqingyun1010jolly@gmail.com
ORCID: https://orcid.org/0009-0000-4207-3513

***Xinmian Cui*** Experimental Kindergarten of Erqi District, Zhengzhou City, P. R. China
E-mail: c754358701@163.com
ORCID: https://orcid.org/0009-0001-4220-7590

***Yanfei Xu*** Faculty of Education, University of Malaya (Universiti Malaya), 50603 Kuala Lumpur, Federal Territory of Kuala Lumpur, Malaysia.
E-mail: S2174359@siswa.um.edu.my
ORCID: https://orcid.org/0009-0000-7985-3126

***Nina Wang*** Faculty of Liberal Arts and Law, Guangdong University of Petrochemical Technology, Maoming, Guangdong, 525000, P. R. China.
E-mail: wqlwnn@gmail.com
ORCID: https://orcid.org/0000-0001-9831-1197

***Mengyan Wang*** Faculty of Education, Universiti Malaya, 50603 Kuala Lumpur, Federal Territory of Kuala Lumpur, Malaysia.
E-mail: wangalisa960@gmail.com
ORCID: https://orcid.org/0009-0001-4459-4512