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PREDICTING TEACHERS' INTENTIONS FOR AIGC INTEGRATION IN PRESCHOOL EDUCATION: A HYBRID SEM-ANN APPROACH

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ABSTRACT

Aim/Purpose	This study investigates the key factors influencing preschool teachers' sustained use of Artificial Intelligence-Generated Content (AIGC) technology in educational settings. While prior research has extensively examined initial adoption, little attention has been given to understanding the continuous intention of preschool teachers with AIGC. To bridge this gap, this study integrates the Technology Acceptance Model (TAM), Expectation-Confirmation Model (ECM), and Flow Theory to develop a comprehensive framework that captures cognitive, affective, and experiential factors shaping continued AIGC adoption.
Background	AIGC has demonstrated immense educational potential, providing personalized learning experiences, real-time feedback, and intelligent student progress tracking. However, most existing research focuses primarily on system usability and feasibility, neglecting the motivational and psychological aspects that determine continuous intention to use AIGC. Specifically, satisfaction, expectation confirmation, and flow experience have been largely overlooked as key determinants of sustained technology use. Given that preschool educators face unique pedagogical challenges, such as adapting AIGC content to young learners and maintaining engagement, understanding the drivers of long-term AIGC use is essential for optimizing its integration into preschool education.
Methodology	This study employs a mixed-method approach to ensure a rigorous and comprehensive analysis. A total of 433 preschool teachers participated in the survey, and Partial Least Squares-Structural Equation Modeling (PLS-SEM) was used to test the hypothesized relationships. To complement structural modeling, Artificial Neural Network (ANN) modeling was applied to uncover non-linear relationships that traditional statistical methods might overlook. By integrating

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PLS-SEM and ANN, this study provides a more robust, predictive, and holistic understanding of the factors driving sustained AIGC adoption.

Contribution

This study makes significant theoretical and practical contributions. Theoretically, it extends TAM and ECM by incorporating Flow Theory. Unlike prior studies focusing primarily on perceived usefulness and ease of use, this research identifies confirmation and satisfaction as the strongest predictors of continued intention to use AIGC. Practically, the findings provide valuable insights for policymakers, school administrators, and ed-tech developers, offering recommendations for designing more engaging, sustainable, and user-friendly AIGC solutions tailored for preschool education.

Findings

The results indicate that satisfaction ($\beta = 0.280$, $p < 0.001$) is the strongest predictor of continued AIGC use, followed by attitude ($\beta = 0.262$, $p < 0.001$) and flow experience ($\beta = 0.223$, $p < 0.001$). Expectation confirmation significantly enhances perceived usefulness ($\beta = 0.505$, $p < 0.001$) and satisfaction ($\beta = 0.349$, $p < 0.001$), reinforcing the importance of aligning AIGC tools with teachers' expectations. ANN analysis further highlights confirmation (95.28%) and satisfaction (82.41%) as the most influential factors, whereas perceived ease of use (22.35%) has a relatively minor impact. These findings suggest that positive user experience, engagement, and expectation fulfillment are key drivers of long-term AIGC adoption. Moreover, ANN analysis revealed complex nonlinear relationships, demonstrating that traditional statistical methods might underestimate the true impact of psychological and experiential factors on technology retention.

Recommendations for Practitioners

For practitioners, this study provides several actionable recommendations. First, AIGC tools should be designed to enhance engagement and intrinsic motivation, integrating gamification elements, interactive features, and adaptive learning support to sustain user interest. Second, ongoing professional development programs should be implemented to train teachers on the pedagogical applications of AIGC, addressing any concerns related to usability or long-term feasibility. Third, AIGC platforms should incorporate customization features, allowing educators to tailor content based on their specific classroom needs and teaching styles. By addressing these factors, AIGC adoption in preschool education can be more sustainable and impactful.

Recommendations for Researchers

For researchers, this study opens multiple avenues for future exploration. First, future research should adopt a longitudinal approach to examine how preschool teachers' attitudes and behaviors toward AIGC evolve over time. Second, more research is needed to explore the role of teacher personality traits and digital literacy levels in shaping AIGC adoption patterns. Third, cross-cultural studies could provide deeper insights into how different educational systems and sociocultural contexts influence preschool teachers' responses to AIGC technologies. Furthermore, AI-driven predictive analytics should be explored to model behavioral trends and optimize AIGC implementations across diverse learning environments.

Impact on Society

This study has significant implications for educational equity, teacher workload, and early childhood learning experiences. By empowering preschool teachers with AIGC, this research promotes more inclusive and accessible preschool education, reducing disparities in educational resources and opportunities. Additionally, AI-driven teaching solutions can alleviate teacher workload, enabling educators to focus on creative and interactive pedagogical strategies rather than

administrative tasks. As AIGC continues to evolve, its potential to transform preschool education into a more engaging, adaptive, and learner-centered experience becomes increasingly evident.

Future Research While this study provides valuable insights into preschool teachers' sustained use of AIGC, several areas require further exploration. First, objective usage data should be incorporated into future research rather than relying solely on self-reported surveys to enhance validity. Second, longitudinal studies should examine how teachers' continuous intention to use AIGC evolves over time in response to technological advancements and policy shifts. Third, as this study focuses on preschool educators, future research should explore whether the identified factors apply to primary and secondary education teachers. Additionally, ethical concerns, AI trust, and data privacy issues should be further investigated, as they may significantly impact the long-term adoption of AIGC in educational settings.

Keywords AI-generated content (AIGC), preschool education, structural equation modeling (SEM), artificial neural networks (ANN)

INTRODUCTION

Artificial Intelligence-Generated Content (AIGC) technology has emerged as a transformative force in education, offering new possibilities for enhancing teaching quality and personalizing learning experiences. AIGC enables the automated generation of text, images, and multimedia content, offering diverse and accessible teaching resources for educators and learners (Chu, 2024; Q. Zhang & Lin, 2024). Beyond content creation, AIGC has been increasingly integrated into intelligent tutoring systems, adaptive learning platforms, and interactive classroom tools, fostering greater engagement and efficiency in learning (Z. Hu, 2024). Studies highlight its potential to improve learning efficiency, reduce teachers' workload, and support the development of 21st-century skills (Xinyu Chen, Yahaya, et al., 2024; G. Lu et al., 2024). However, despite these advantages, how and why teachers adopt and continue using AIGC remains an open question, particularly in preschool education.

While AIGC adoption has been extensively examined in higher education and K-12 settings, its implementation in preschool education remains largely underexplored. Preschool education plays a fundamental role in fostering children's cognitive, social, and emotional development (Rose-Krasnor & Denham, 2009). However, preschool teachers face unique pedagogical and technological challenges, including limited digital literacy, the need for age-appropriate content, and play-based instructional methodologies (Farisia & Syafi'i, 2024; Stewart, 2024). Unlike higher education, where digital tools are seamlessly integrated, preschool teachers must navigate institutional and instructional barriers that shape their technology adoption behaviors. Existing research on technology adoption often assumes homogeneous adoption patterns across educational levels. However, the factors influencing preschool teachers' acceptance and sustained use of AIGC may differ significantly from those in K-12 and higher education settings. This knowledge gap underscores the necessity of investigating AIGC's continuous adoption in preschool contexts, ensuring that AI-driven tools align with early childhood education principles.

A major limitation of prior research is the moderate explanatory power of existing adoption models, with R^2 values typically ranging from 0.42 to 0.48. For example, one study using UTAUT2 with an IS model reported an R^2 of 0.4778, indicating limited predictive power (Mohd Rahim et al., 2022). Another study incorporating UTAUT2 alone achieved an R^2 of 0.429 (L. Hu et al., 2025). These findings suggest that while prior studies have contributed valuable insights, they may not have fully captured the complexities of technology adoption. Additionally, most models have primarily focused on cognitive determinants such as perceived usefulness and ease of use, while neglecting affective and contextual influences. For instance, previous research applying TAM did not incorporate ECM or Flow Theory, potentially overlooking key psychological factors influencing sustained adoption (Lai et al., 2023). Similarly, models employing ECM and UTAUT2 have failed to account for user engagement and satisfaction, which are critical in predicting long-term technology use (Tian et al., 2024). Given these limitations, there is a need for a more comprehensive model that integrates both cognitive and affective determinants to improve explanatory power and predictive accuracy.

To bridge this gap, this study integrates TAM, ECM, and Flow Theory to examine the determinants of preschool teachers' sustained use of AIGC. TAM provides a foundational framework for understanding initial adoption behaviors through perceived usefulness and ease of use, while ECM extends this by considering post-adoption factors such as confirmation and satisfaction. Flow Theory further enhances the model by capturing affective dimensions of engagement and immersion, which are critical for sustained technology use. Empirical findings indicate that this integrated model achieves an R^2 of 0.518 for Continued Intention to Use (CITU), significantly improving explanatory power compared to previous models. This suggests that, beyond traditional cognitive predictors, affective factors such as satisfaction and flow experience play a crucial role in predicting preschool teachers' sustained use of AIGC.

Behavioral intention to use AIGC is a crucial variable in technology adoption studies, as it strongly predicts actual technology adoption and long-term utilization in educational settings. According to TAM, behavioral intention directly influences actual usage behavior, making it a key determinant of technology adoption (Davis, 1989; Davis et al., 1989). In preschool education, where teachers operate in highly interactive and child-centered learning environments, behavioral intention provides key insights into both adoption barriers and facilitators. This study helps bridge the gap between technological advancements and practical preschool pedagogy by analyzing intention to use as the outcome variable.

To address these questions, this study adopts a hybrid SEM-ANN approach, which combines Structural Equation Modeling (SEM) and Artificial Neural Networks (ANN) to provide both explanatory and predictive insights into preschool teachers' sustained adoption of AIGC. SEM is a statistical technique that allows researchers to test hypothesized relationships among constructs within a theoretical framework, enabling the analysis of both direct and indirect effects. In contrast, ANN is a machine learning method that excels at modeling complex, nonlinear patterns, thereby improving prediction accuracy beyond the capabilities of traditional linear models. By integrating these two methods, the study not only validates causal pathways through SEM but also enhances the robustness of findings through ANN-based prediction of behavioral intention outcomes.

This study contributes to both theoretical and practical domains. From a theoretical perspective, this study extends the TAM framework by integrating ECM to account for the role of confirmation and satisfaction in the sustained use of AIGC. Additionally, it introduces Flow Theory to capture the impact of engagement and immersion on technology adoption. While previous studies have primarily examined these frameworks in higher education settings, this study adapts them to the preschool context, considering the distinct needs and challenges of early childhood educators. Furthermore, the findings of this study are generalizable beyond preschool education. While the primary focus is on early childhood educators, the integrated model of TAM, ECM, and Flow Theory is applicable to broader educational settings where technology adoption involves a mix of cognitive and affective factors. This makes the study highly relevant to both academia and industry, as understanding technology adoption mechanisms can enhance AI-driven tool implementation across various sectors. The integration of TAM, ECM, and Flow Theory offers a more comprehensive framework for analyzing AIGC's continuous adoption across various educational levels, particularly in settings that emphasize interactive, student-centered pedagogies.

Beyond theoretical contributions, this study offers practical implications for policymakers and technology developers. Policymakers can leverage these insights to design more effective professional development programs that enhance preschool teachers' digital competence and confidence in using AIGC tools. Additionally, technology developers can design AI-driven educational tools that align with pedagogical best practices and cater to the unique needs of preschool teachers. By identifying the key enablers and barriers of AIGC sustained adoption, this study enhances existing technology acceptance models and offers a framework for supporting AI adoption in various educational contexts.

LITERATURE REVIEW

The integration of AIGC into education has gained increasing attention, with governments and educational institutions actively leveraging this technology to enhance teaching quality and learning outcomes (W. Yang et al., 2024). AIGC provides advanced capabilities such as personalized content generation, real-time feedback, and intelligent student progress tracking, all of which contribute to more adaptive and engaging learning environments (Dai et al., 2023; G. Lu et al., 2024; Wei & Qi, 2024). Governments worldwide are making substantial investments in educational technology, recognizing its potential to drive innovation in teaching methodologies and improve overall educational effectiveness (Ahmed & Meraj, 2024). Studies have shown that AIGC-supported instruction significantly enhances student engagement and learning outcomes compared to traditional teacher-centered approaches (P. Mishra, 2025; Rong et al., 2024).

In preschool education, AIGC has been shown to foster creativity, personalized learning, and interactive storytelling, making it a valuable pedagogical tool (Y. Bai, 2024; Xiaojiao Chen, Hu, et al., 2024; T. Ma et al., 2023). Studies indicate that AIGC-driven personalized learning environments can enhance children's cognitive development and improve teacher-student interaction by providing tailored instructional content (J. Bai et al., 2025; Li et al., 2024; Zhao et al., 2024). However, despite these advantages, many preschool educators hesitate to integrate AIGC into their daily teaching due to concerns about workload, technological complexity, and long-term feasibility (Dennard, 2024). This raises critical questions regarding what factors influence preschool teachers' sustained use of AIGC and how these factors shape their behavioral intentions. Addressing these questions is essential for ensuring the long-term effectiveness of AIGC in preschool education.

AIGC applications in education extend beyond automated content generation to personalized learning support and interactive teaching strategies. Various studies have explored AIGC's role in curriculum design, adaptive learning, and intelligent tutoring systems (Dai et al., 2023; Huang et al., 2024). However, while much research has focused on the technical affordances of AIGC, there is a significant gap in understanding the behavioral and psychological factors influencing teachers' continued use of this technology. Specifically, existing research has yet to identify the key factors that influence preschool teachers' sustained intention to use AIGC and how these factors shape their behavioral intentions. Most prior studies have primarily examined the initial adoption phase, focusing on factors such as system usability and implementation feasibility (C. Wang et al., 2025; S.-F. Wang & Chen, 2024; X. Yang et al., 2024; X. Zhang et al., 2024). However, the determinants of continuous intention to use – including the role of cognitive evaluations (e.g., perceived usefulness, perceived ease of use), affective responses (e.g., satisfaction, attitude), and experiential factors (e.g., flow experience, expectation confirmation) – remain insufficiently addressed. Given that continued use is essential for the successful integration of AIGC into preschool education, further investigation into these influencing factors is warranted. Table 1 summarizes key past studies on technology adoption in education, highlighting their methodologies, key variables, and major findings.

These studies have laid the groundwork for understanding technology adoption in education, but have not sufficiently addressed the long-term use of AIGC among preschool teachers. This study aims to bridge this gap by integrating key theoretical perspectives to explain sustained AIGC adoption.

Table 1. Key past studies of continuous intention to use AIGC

Study	Methods	Key variables	Findings	Limitations
Zheng et al. (2024)	PLS-SEM	PU, SAT, CON, CITU	PU was the most direct factor to CITU	Did not examine engagement factors like Flow Did not examine PEOU in TAM
H. Lu et al. (2024)	PLS-SEM	PU, PEOU, AT, CITU	Intentions to use AIGC technology were primarily influenced by PU, PEOU, AT	Did not examine engagement factors like Flow Did not examine factors in ECM
Peng et al. (2024)	PLS-SEM	PU, PEOU, SAT, AT, CON, CITU	PU, SAT, PEOU directly influenced CITU	Did not examine engagement factors like Flow
Soliman et al. (2024)	PLE-SEM, ANN	PU, PEOU, CITU	PU directly influenced CITU PU and PEOU were the strongest predictors of continuous intention to use AIGC	Did not examine engagement factors like Flow Did not examine factors in ECM
Yu et al. (2024)	SEM	PU, PEOU, SAT, CITU	PEOU and PU were identified as core factors affecting users' SAT and CITU	Did not examine engagement factors like Flow Did not examine some factors in ECM
Pasupuleti and Thiyyagura (2024)	SEM	PU, PEOU, SAT, AT, CON, CITU	PU, AT, and SAT were significant predictors of CITU	Did not examine engagement factors like Flow
Current study (this study)	PLS-SEM, ANN	PU, PEOU, SAT, AT, CON, CITU	CON and SAT were the strongest predictors of sustained AIGC adoption SAT, PU, AT, and FLO directly influenced continuous intention	Addresses preschool teachers' context, integrates ANN for predictive analysis

Several key factors have been discussed in the literature as critical to sustained technology use. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) originate from the Technology Acceptance Model (TAM) (Davis, 1989) and are commonly used to explain user adoption of technology. PU refers to the extent to which users believe that using technology will enhance their performance, while PEOU measures the ease with which users can interact with technology (Davis, 1989). Research has consistently shown that PU and PEOU are strong predictors of initial technology adoption (Cho & Hung, 2009; Kampa, 2023; Scherer & Teo, 2019). However, existing studies have largely overlooked their long-term effects on continuous usage, particularly in the context of preschool education.

Attitude (AT) and Satisfaction (SAT) are also key determinants of technology adoption. Attitude reflects users' overall evaluation of technology and significantly influences their willingness to continue using it (Teo & Noyes, 2011). Satisfaction, a core component of the Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001), determines whether users continue using technology based on their experience. While many studies have confirmed the role of satisfaction in educational technology adoption, few have examined its long-term effects in preschool settings.

Flow Experience (FLO) and Confirmation (CON) have been widely studied in educational technology adoption. Flow Theory suggests that individuals who experience deep engagement and enjoyment while using technology are more likely to continue using it (Nakamura & Csikszentmihalyi, 2009). Flow is particularly relevant to AIGC, as the technology offers immersive and interactive learning experiences (Wen et al., 2024). Teachers who experience high levels of engagement with AIGC-based teaching tools are more likely to sustain their usage. Additionally, Confirmation (CON) refers to the extent to which users' expectations align with their actual experiences, which in turn affects their satisfaction and sustained usage (Bhattacherjee, 2001). Empirical evidence suggests that confirmation enhances perceived usefulness, which ultimately leads to long-term technology retention (Song et al., 2023; Tam et al., 2020).

Despite the extensive literature on technology adoption, significant gaps remain in understanding preschool teachers' long-term engagement with AIGC. Furthermore, while PU and PEOU have been widely studied, the combined influence of cognitive, affective, and experiential factors on sustained AIGC use remains underexplored. Additionally, few studies have specifically examined AIGC adoption in preschool education, where teaching methodologies and user experiences differ significantly from those in higher education settings.

To address these gaps, this study is guided by the following research questions:

(1) What are the key factors influencing preschool teachers' sustained use of AIGC technology?

(2) How do these factors shape preschool teachers' behavioral intentions toward AIGC?

By integrating TAM, ECM, and Flow Theory, this study provides a comprehensive understanding of preschool teachers' sustained use of AIGC, addressing both rational evaluations and emotional engagement. The findings will not only advance theoretical understanding but also offer practical insights for educators, policymakers, and developers in fostering the long-term adoption of AI-based educational tools.

RESEARCH MODEL AND HYPOTHESIS

CONFIRMATION (CON)

Confirmation refers to users' perception of consistency between their actual experience with technology and their initial expectations. This concept originates from Expectation Confirmation Theory and has been widely applied in the fields of information systems and technology adoption to explain the mechanisms behind satisfaction and continued usage behavior (Hossain & Quaddus, 2012). In the educational context, confirmation primarily reflects users' affirmation of a technology's functionality, reliability, and suitability for teaching after use.

Studies on technology applications indicate that confirmation significantly influences perceived usefulness and satisfaction. For instance, C. Schwarz and Zhu (2015) found that students' confirmation of technology directly enhanced their perception of its actual value in classroom teaching. This sense of value subsequently translated into higher satisfaction and continued usage intention. Similarly, Toros et al. (2024) demonstrated that when users feel that a technology meets their needs and aligns with their expectations, their satisfaction increases significantly, leading to a more positive attitude toward long-term usage. These findings highlight the critical role of confirmation as a core variable influencing perceived usefulness and satisfaction. Its mechanism is of great importance for research and practice in technology adoption in preschool education.

H1: Confirmation positively influences Perceived Usefulness.

H2: Confirmation positively influences Satisfaction.

Flow Theory (FLO)

Flow experience, derived from Nakamura and Csikszentmihalyi's (2009) Flow Theory, refers to a psychological state where individuals are fully immersed, focused, and experience enjoyment during an activity. This theory has been widely applied in the field of educational technology, particularly in analyzing how technology enhances learners' and educators' active engagement and motivation. Flow experience is considered a critical factor influencing users' attitudes toward technology and their behavioral intentions, as it allows users to perceive the value of technology through an enjoyable experience (Wu et al., 2024).

In the educational context, flow experience often manifests as users' deep engagement with technology and their satisfaction with the outcomes. For example, when users achieve a state of flow during technology-supported activities, they focus on how the technology enhances interaction and creates a more engaging environment (X. Yang et al., 2018). This immersion not only fosters a positive attitude toward the technology but also strengthens their intention to continue using it. Liu et al. (2009) found that flow experience plays a significant role in promoting technology acceptance and shifting user attitudes positively.

Xu et al. (2024) demonstrate that when users experience flow while using technology and perceive its innovation and convenience, they are more likely to exhibit continued usage intentions. Moreover, the indirect influence of flow experience on attitude and intention has been widely validated. For instance, D. Lee (2022) proposed that the flow experience enhances users' interest and satisfaction, which in turn strengthens their support and acceptance of the technology. In the context of preschool education, AIGC technology can provide higher flow experiences for teachers through personalized content generation and interactive design. This not only improves teaching quality but also inspires teachers' professional creativity.

H3: Flow experience positively influences Continued Intention to Use.

H4: Flow experience positively influences Attitude.

Attitude (AT)

Attitude is one of the key factors determining users' acceptance and intention to continue using a technology. It is defined as the overall evaluation of a technology, encompassing positive or negative emotional tendencies (N. Schwarz & Bohner, 2001). In the TAM, attitude is considered a critical mediating variable that links perceived usefulness and perceived ease of use to behavioral intention (Davis, 1993). In the educational context, teachers' attitudes toward AIGC technology reflect their subjective perception of whether the technology can effectively support teaching, enhance classroom interaction, and meet instructional needs.

Existing research indicates that attitude has a significant positive influence on continued usage intention. For instance, Chan and Hu (2023) found that when users have a positive attitude toward technology, they are more likely to integrate it into practice and exhibit stronger continued usage intentions. Similarly, some studies also emphasized that positive attitudes toward technology are primarily driven by intuitive design, notable practical value, and low operational complexity (Kaya et al., 2024; J. Wang et al., 2024). Moreover, the mediating role of attitude between perceived usefulness and behavioral intention has been widely validated. Labrague et al. (2023) demonstrated that when users perceive a technology as easy to use and useful, these perceptions enhance their attitude, which in turn influences their intention to use the technology. As a strong predictive variable, attitude plays a critical role in promoting the adoption of AIGC technology and advancing educational technology development.

H5: Attitude positively influences Continued Intention to Use.

Perceived Ease of Use (PEOU)

Perceived Ease of Use plays a critical role in influencing users' acceptance and adoption of technology. TAM, introduced by Davis et al. (1989), highlights the significant impact of PEOU on users' attitudes and intentions to adopt technology. In the educational context, particularly for preschool teachers, the intuitiveness and ease of use of AIGC technology are considered essential factors for its successful integration.

Studies in the educational domain further support this perspective. For example, Hwa et al. (2015) demonstrated that the higher the perceived ease of use of educational technology, the more likely users are to accept it. In educational settings, the simplicity of operation and user-friendly interface design are especially critical, as users may lack advanced technical skills. Saadé and Bahli (2005) found that when target groups perceive technology as easy to use, they are more inclined to adopt it. These findings underline the importance of developing intuitive and efficient AIGC technology interfaces and support systems tailored for preschool education. Such efforts can enhance teachers' positive experiences and promote the widespread adoption of AIGC technologies.

H6: Perceived Ease of Use positively influences Attitude.

H7: Perceived Ease of Use positively influences Perceived Usefulness.

Perceived Usefulness (PU)

Perceived Usefulness is a critical determinant of technology acceptance, reflecting the belief that a specific technology or system can enhance efficiency or effectiveness. In the context of applying AIGC technology in preschool education, PU primarily represents preschool teachers' perception of AIGC systems as valuable tools for improving teaching outcomes, optimizing educational resources, and enhancing classroom interaction. Davis et al. (1989) introduced PU in the TAM, asserting its significant influence on technology adoption. This theory has been widely validated in educational settings.

Research on technology integration in education demonstrates that PU plays a central role in shaping users' intention to use technology. For instance, Tahar et al. (2020) found that users' perception of a technology's usefulness significantly affects their intention for continuous use. Similarly, L. Ma and Lee (2019) investigated the PU of educational technologies among target groups and revealed that when a technology is perceived to effectively support learning goals, users are more likely to adopt it for long-term use. This indicates that the potential of AIGC technology to enhance teaching efficiency and enrich educational resources can motivate teachers to adopt it continuously. Therefore, developing AIGC systems that effectively meet teaching needs and significantly improve educational outcomes is essential for promoting their widespread application in preschool education.

H8: Perceived Usefulness positively influences Continuous Use Intention.

H9: Perceived Usefulness positively influences Attitude.

H10: Perceived Usefulness positively influences Satisfaction.

Satisfaction (SAT)

Satisfaction refers to the overall evaluation of a user's experience with technology and is one of the critical determinants of the intention to continue using the technology. Within the framework of the ECM, satisfaction is defined as a positive response to the perceived value and experience of using technology, serving as a key factor influencing continuous use intention (Jo, 2023). In the context of preschool education, teachers' satisfaction with AIGC technology reflects its ability to meet educational needs, provide effective support, and enhance classroom outcomes.

Existing research highlights satisfaction as a significant driver of continued technology use intention. For example, Xie et al. (2023) demonstrated that users' satisfaction while using a technology significantly enhances their intention for long-term use. Satisfaction often stems from the technology's stability, functional suitability, and the quality of support services. Pyae et al. (2023) found that when a technology is seamlessly integrated into activities and offers convenience to users, their satisfaction significantly improves. Furthermore, J.-C. Lee et al. (2023) revealed that confirmation has a significant positive impact on satisfaction. This means that when users' actual experiences meet or exceed their expectations, their satisfaction increases. In the educational application of AIGC technology, heightened satisfaction not only directly drives teachers' continuous use intentions but also fosters trust and recognition, further motivating them to explore innovative applications of the technology.

H11: Satisfaction positively influences Continuous Use Intention.

Figure 1 illustrates the model developed in this study.

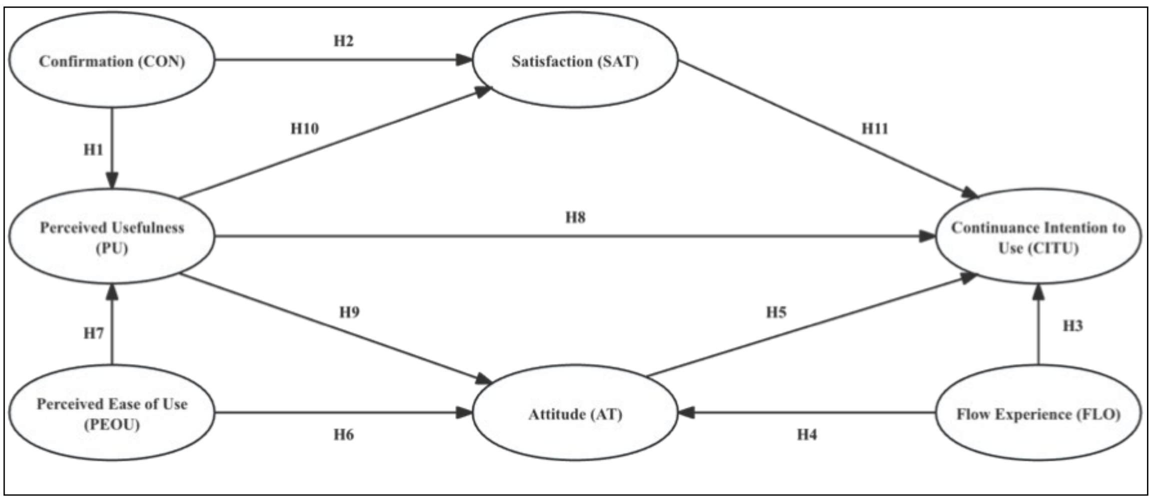

Figure 1. Research model

METHODOLOGY

PARTICIPANTS AND DATA COLLECTION

This study employed a purposive sampling approach to ensure that participants were relevant to the research objectives. The target population consisted of preschool teachers across various urban and rural regions in China, covering both public and private preschool institutions. Given that AIGC is an emerging technology in preschool education, this study did not assume that all participants had extensive hands-on experience with AIGC. Instead, a screening question was incorporated into the questionnaire to confirm that respondents had interacted with AIGC in some capacity, whether through direct classroom integration, professional training workshops, or pilot programs conducted in their institutions. This ensured that all participants had at least a basic understanding of AIGC, enabling them to provide informed responses regarding their perceptions and adoption behaviors.

To ensure statistical robustness, this study used G*power software to determine the required sample size. Based on a medium effect size of 0.15, a significance level of 0.05, a statistical power of 0.95, and nine predictors (Lubis et al., 2024), the minimum sample size required was 166. However, recommendations for complex SEM models suggest a minimum of 200 participants (Shaninah & Mohd Noor, 2024) and an optimal sample size of approximately 400 (Lund, 2023).

The questionnaire was distributed online via Google Forms, with invitations sent through teacher associations, educational institutions, and professional networks. A total of 500 responses were initially collected. However, 67 responses were excluded due to incomplete answers or refusal to participate, resulting in a final valid sample of 433 preschool teachers. This sample size exceeded the recommended minimum and ensured reliable parameter estimation in PLS-SEM analysis.

To enhance the generalizability of findings, participants were recruited from both urban and rural regions across public and private preschools. This geographic and institutional diversity allows for a broader understanding of AIGC adoption patterns across different educational contexts. As shown in Table 2, the sample consisted of 59.8% female teachers (259 respondents) and 40.1% male teachers (174 respondents). The respondents' ages ranged from 20 to over 50 years, representing teachers at different career stages. In terms of educational background, 58.4% held a bachelor's degree, 33.7% a master's degree, and 7.8% a doctoral degree. By ensuring that all respondents had some level of familiarity with AIGC while capturing diverse perspectives across different teaching environments, this study establishes a strong empirical foundation for analyzing AIGC adoption in preschool education.

Table 2. Demographic profile

Demographic profile	Frequency	Percentage
Gender		
Male	174	40.1
Female	259	59.8
Age		
20-29 years	50	11.5
30-39 years	344	79.4
40-49 years	24	5.5
Above 50 years	15	3.4
Educational Level		
Bachelor	253	58.4
Master	146	33.7
PhD	34	7.8

Instrument

This study used a questionnaire to test the research hypotheses, selecting seven key constructs as measurement criteria, each derived from previously validated studies. Based on the AIGC adoption factors listed in Table 3, the questionnaire consisted of 24 items. To ensure the accuracy and relevance of the items, this study refined the questionnaire by referencing prior research. The data collection instrument was divided into two sections. The first section gathered basic demographic information about the respondents, including gender, age, and educational background. The second section measured factors influencing respondents' continued adoption of AIGC technology in preschool education. Responses were recorded on a five-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree), capturing teachers' perceptions.

Table 3. Measurement items

Constructs	Items	Instrument	Sources
Perceived ease of use	PEOU1	I find it easy to master and use AIGC technology in teaching activities.	(Davis, 1989; Davis et al., 1989)
	PEOU2	The user interface of AIGC technology is intuitive and easy for me.	
	PEOU3	Using AIGC technology in teaching does not require brainpower.	
	PU1	Using AIGC technology in teaching makes it easier for me to create instructional materials.	

Constructs	Items	Instrument	Sources
Perceived usefulness	PU2	Using AIGC technology has enhanced my teaching skills and educational knowledge.	(Davis, 1989; Davis et al., 1989)
	PU3	AIGC technology can save my time and improve efficiency in teaching.	
Attitude	AT1	AIGC technology makes teaching more interesting.	(Teo et al., 2009)
	AT2	Teaching with AIGC technology is fun.	
	AT3	I like using AIGC technology	
Satisfaction to use	SAT1	I am satisfied with my experience using AIGC technology in education.	(Spreng & Olshavsky, 1993)
	SAT2	I am satisfied with the functions of AIGC technology in education.	
	SAT3	I am satisfied with the overall use of AIGC technology in education.	
Continuance intention to use	CITU1	I intend to use AIGC technology frequently in my future teaching.	(Bhattacherjee, 2001)
	CITU2	I plan to use AIGC technology regularly in my teaching practice in the future.	
	CITU3	I would strongly recommend AIGC technology in education to others.	
Flow experience	FLO1	Using AIGC technology in education makes me fully immersed, often losing awareness of my surroundings.	(Jackson & Marsh, 1996)
	FLO2	When using AIGC in education, I become so engaged that I lose track of time.	
	FLO3	When I use AIGC in teaching, I feel deeply focused and absorbed.	
Confirmation	CON1	I found that using AIGC in education was better than I expected.	(Bhattacherjee, 2001)
	CON2	AIGC technology in education is more interesting than I expected.	
	CON3	AIGC technology in education met my expectations.	

DATA ANALYSIS

This study employed a quantitative research approach to examine preschool teachers' continued adoption of AIGC technology. A two-stage analytical framework was implemented, integrating Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Networks (ANN) to provide both theoretical validation and predictive modeling.

PLS-SEM was used to analyze the relationships between latent constructs and test the proposed hypotheses. SEM is a statistical technique that allows researchers to examine complex causal relationships among multiple variables, estimate latent variables, and assess measurement models (Al Masud et al., 2024). PLS-SEM was selected due to its suitability for analyzing complex models with latent variables and its ability to handle non-normally distributed data (Hair & Alamer, 2022). Compared to covariance-based SEM (CB-SEM), PLS-SEM is more appropriate when data normality assumptions cannot be strictly met and when the research aims to maximize explained variance (R^2) rather than model fit (Wah, 2025). Given that this study integrates constructs from TAM, ECM, and Flow Theory, PLS-SEM provides an effective approach to simultaneously assess measurement and structural models.

The analysis was conducted using SmartPLS 4.0, following a two-stage approach. First, the measurement model was evaluated to ensure its reliability and validity. Next, the structural model was tested to examine the relationships among the study variables. Reliability and validity of the measurement model were assessed using SmartPLS, with a factor loading threshold of 0.7 (Beldiq et al., 2024). Collinearity issues were examined through VIF values, with all final items showing VIF values below 3.30. Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE) were evaluated against thresholds of 0.7 and 0.5, respectively (Al-Zwainy & Al-Marsomi, 2023; Beldiq et al., 2024). Discriminant validity was established using the Fornell-Larcker criterion, assessing the square correlations among latent variables (Cheung et al., 2024). These validity and reliability tests confirm the robustness of the measurement model. For the structural model, bootstrapping with 5,000 resamples was used to estimate path coefficients and determine their significance levels. The model's explanatory power was assessed using R^2 values, measuring the proportion of variance explained by the predictor variables. Additionally, predictive relevance (Q^2 values) was examined, ensuring that the model exhibited sufficient out-of-sample predictive accuracy.

Although PLS-SEM is effective for testing causal relationships, its reliance on linear modeling may oversimplify complex adoption behaviors. To address this limitation, ANN was incorporated as a complementary analytical technique to capture nonlinear patterns in adoption behavior. ANN, inspired by the structure of the human brain, is a machine learning algorithm capable of modeling complex nonlinear relationships between inputs and outputs (Schmidgall et al., 2024). The ANN model was designed using a multilayer perceptron (MLP) network, optimized to achieve high predictive accuracy. The input layer comprised the predictor variables identified through PLS-SEM. The output layer was configured to predict continued intention to use AIGC as a continuous variable. The dataset was randomly split into 70% training and 30% validation sets to minimize overfitting (W. Chen et al., 2017). Model performance was evaluated using Root Mean Square Error (RMSE) and R^2 values, confirming the predictive strength of key determinants.

By integrating PLS-SEM and ANN, this study presents a comprehensive methodological framework that enhances both theoretical validation and predictive modeling. PLS-SEM facilitates hypothesis-driven theory testing, while ANN enhances predictive accuracy and uncovers nonlinear interactions that may be overlooked in traditional SEM approaches.

RESULTS

RELIABILITY, NORMALITY, AND VALIDITY

Table 4 presents the results of reliability and validity measurements. CA and CR values are all above 0.7, indicating good internal consistency of the measurement items for each construct (Kainde & Mandagi, 2023). Convergent validity requires an AVE value greater than 0.50, and all constructs in this study meet this criterion, demonstrating satisfactory convergent validity (Baharum et al., 2023).

Table 4. Cronbach's alpha, composite reliability, and average variance extracted

Variables	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Perceived ease of use (PEOU)	0.826	0.896	0.742
Perceived usefulness (PU)	0.823	0.895	0.739
Attitude (AT)	0.860	0.915	0.781
Satisfaction to use (SAT)	0.912	0.944	0.850
Continuance intention to use (CITU)	0.896	0.935	0.828
Flow experience (FLO)	0.829	0.894	0.739
Confirmation (CON)	0.901	0.938	0.835

Furthermore, Table 5 presents the discriminant validity results (bolded diagonal values), showing that the square root of the AVE for each latent variable exceeds its correlation with other latent variables. This confirms that the discriminant validity among the latent variables has been established, which is in line with the Fornell-Larcker criterion (Fornell & Cha, 1994). This method remains widely used for assessing discriminant validity in structural equation modeling (Hair et al., 2021).

Table 5. Discriminant validity Fornell-Larcker criterion

	AT	CITU	CON	FLO	PEOU	PU	SAT
AT	**0.884**						
CITU	0.604	**0.910**					
CON	0.638	0.647	**0.914**				
FLO	0.427	0.524	0.520	**0.859**			
PEOU	0.345	0.172	0.309	0.083	**0.861**		
PU	0.661	0.534	0.553	0.364	0.312	**0.860**	
SAT	0.554	0.605	0.520	0.493	0.176	0.502	**0.922**

MODEL FIT

In PLS-SEM, the R^2 value serves as a key indicator of model explanatory power, reflecting the extent to which the independent variables explain the variance of the dependent variables. According to (Henseler et al., 2009), an R^2 value above 0.50 is considered high, while values between 0.25 and 0.50 indicate moderate explanatory power, and values below 0.25 are weak.

In this study, the R^2 value for CITU was 0.519, indicating that the model explains 51.9% of the variance in continued intention to use AIGC. This falls within the high explanatory power range, demonstrating that the model effectively captures key determinants of AIGC adoption. Compared to previous studies on technology adoption (e.g., L. Hu et al., 2025; Mohd Rahim et al., 2022), where R^2 values typically ranged from 0.42 to 0.48, the present study exhibits relatively stronger explanatory power. This suggests that the integration of TAM, ECM, and Flow Theory provides a more comprehensive understanding of AIGC adoption. However, approximately 48.1% of the variance remains unexplained, indicating that future research could explore additional determinants, such as external environmental factors or institutional support.

Similarly, the R^2 value for AT was 0.500, indicating moderate-to-strong explanatory power for attitude toward AIGC, which aligns with previous findings in AI adoption (Distor et al., 2021). For PU ($R^2 = 0.328$) and SAT ($R^2 = 0.335$), the model explains approximately 32.8% and 33.5% of their variance, respectively, which falls into the moderate range. While these values indicate a reasonably good fit, future research could explore additional antecedents to further improve the explanatory power of these constructs.

To assess the predictive relevance (Q^2) of the model, the blindfolding procedure was applied. According to Manfrin (2023), Q^2 values above 0.35 indicate strong predictive relevance, values between 0.15 and 0.35 suggest moderate predictive relevance, and values below 0.15 indicate weak predictive power.

The Q^2 value for CITU was 0.421, and for AT, it was 0.384, both of which exceed the 0.35 threshold, indicating strong predictive relevance. These results confirm that the model provides reliable predictive capability for continued intention to use AIGC and attitude toward AIGC.

For SAT ($Q^2 = 0.283$) and PU ($Q^2 = 0.235$), the predictive relevance falls within the moderate range ($0.15 \leqslant Q^2 < 0.35$), indicating that the model captures some predictive power, but additional variables may enhance its accuracy. The discrepancy between the moderate R^2 values for PU and SAT and their corresponding Q² values suggests that while the model provides explanatory power, additional contextual or motivational factors may improve its predictive accuracy in future research. Since all Q² values exceed zero, these results confirm that the model has meaningful predictive capability for these variables (Ramayah et al., 2018).

Overall, the R² and Q² results suggest that the model possesses moderate-to-strong explanatory power and predictive relevance, particularly for CITU and AT, while further refinements may be necessary to enhance its predictive accuracy for PU and SAT.

PATH ANALYSIS AND HYPOTHESIS TESTING

Figure 2 displays the structural model and path coefficients, illustrating the relationships among key factors influencing preschool teachers' continued intention to use AIGC technology. The results show that all hypothesized relationships were statistically significant, with path coefficients ranging from 0.139 to 0.530. Table 6 presents the hypothesis testing results using bootstrapping (5,000 resamples), confirming the significance of all proposed relationships.

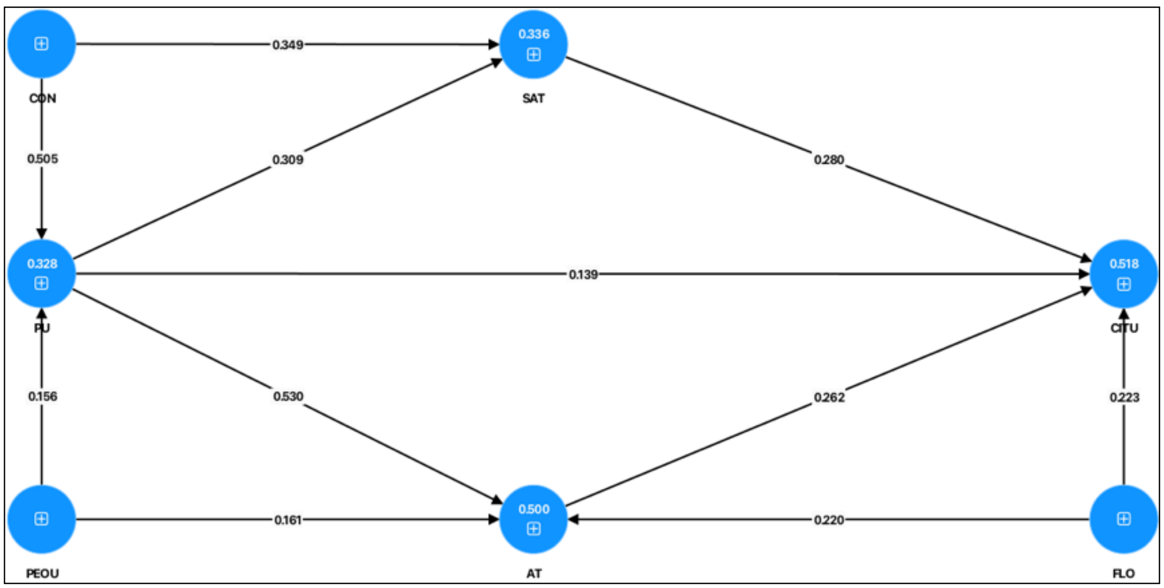

Figure 2. Structural model analysis

The strongest predictor of continued intention to use (CITU) was satisfaction (SAT → CITU, β = 0.280, $p < 0.001$), followed by attitude (AT → CITU, β = 0.262, $p < 0.001$) and flow experience (FLO → CITU, β = 0.223, $p < 0.001$). These results suggest that teachers who are satisfied with AIGC and develop a positive attitude toward it are more likely to continue its use in educational settings. The role of satisfaction and attitude in technology adoption has been well established in previous research (Baig & Yadegaridehkordi, 2025; Jo, 2022), reinforcing the importance of ensuring a positive user experience in AIGC implementation.

Perceived usefulness (PU) significantly influenced attitude (PU → AT, β = 0.530, $p < 0.001$) and satisfaction (PU → SAT, β = 0.309, $p < 0.001$), which aligns with existing studies on technology acceptance, emphasizing the importance of users' perceptions of usefulness in shaping attitudes and overall satisfaction (Berlianto et al., 2024). Interestingly, PU also had a direct, albeit weaker, impact on CITU (PU → CITU, β = 0.139, $p < 0.05$). This indicates that while perceived usefulness contributes directly to continued usage, its primary influence is exerted through attitude and satisfaction, acting as mediators in the adoption process. Prior research has similarly found that PU plays a more dominant role in shaping attitudes rather than directly influencing behavioral intention (Mustofa et al., 2025).

Confirmation (CON) was found to have a significant impact on both PU ($\beta = 0.505$, $p < 0.001$) and SAT ($\beta = 0.349$, $p < 0.001$), supporting the Expectation-Confirmation Model (ECM) perspective that when users' initial expectations are met, they develop a stronger perception of usefulness and higher satisfaction, which in turn drives continued use intentions (Luo et al., 2024; Tsai et al., 2020).

Flow experience (FLO) was a significant predictor of both CITU (FLO → CITU, $\beta = 0.223$, $p < 0.001$) and attitude (FLO → AT, $\beta = 0.220$, $p < 0.001$). These findings suggest that when teachers feel deeply engaged while using AIGC, they are more likely to develop positive attitudes toward the technology and sustain its adoption. Prior studies have also indicated that flow experience enhances engagement, making it a crucial factor in technology adoption (Goh & Yang, 2021).

Interestingly, perceived ease of use (PEOU) had weaker direct effects on AT ($\beta = 0.161$, $p < 0.01$) and PU ($\beta = 0.156$, $p < 0.01$). This suggests that while ease of use is important, its impact on behavioral intention is largely mediated through PU and AT. Unlike prior studies, which found that users adopt technology only when both perceived usefulness (PU) and perceived ease of use (PEOU) are favorable (Ajibade, 2018; Yao et al., 2024), this study suggests a more nuanced relationship.

These results validate all hypotheses proposed in this study, confirming that H1 through H11 are supported. However, the weaker impact of PEOU suggests that future research could explore how external factors such as training programs or institutional support influence teachers' perceptions of AIGC usability.

Table 6. Hypothesis testing

Hypothesis	Relationship	Coefficient (β)	P values	T statistics	Remark
H1	CON→PU	0.505	0.000	10.935	Supported
H2	CON→SAT	0.349	0.000	6.341	Supported
H3	FLO→CITU	0.223	0.000	5.196	Supported
H4	FLO→AT	0.220	0.000	5.559	Supported
H5	AT→CITU	0.262	0.000	4.457	Supported
H6	PEOU→AT	0.161	0.000	4.405	Supported
H7	PEOU→PU	0.156	0.000	3.507	Supported
H8	PU→CITU	0.139	0.009	2.610	Supported
H9	PU→AT	0.530	0.000	12.652	Supported
H10	PU→SAT	0.309	0.000	5.708	Supported
H11	SAT→CITU	0.280	0.000	5.457	Supported

Artificial Neural Network (ANN) Modelling

To complement Partial Least Squares Structural Equation Modeling (PLS-SEM) and enhance predictive accuracy, this study employed Artificial Neural Networks (ANNs). The ANN models were executed using IBM SPSS Statistics, specifically leveraging the Multilayer Perceptron (MLP) network (Malik et al., 2021). The Sigmoid activation function was applied in both the hidden layer and output layer, ensuring smooth nonlinear transformations and bounded outputs within the range of (0,1). This choice of function is commonly used in classification and predictive modeling where probability-based interpretations are necessary (A. Mishra et al., 2017).

To prevent overfitting, the dataset was randomly split into 70% for training and 30% for testing, following established guidelines in ANN applications (Lilhore et al., 2023). Additionally, a 10-fold cross-validation technique was employed to improve generalizability and reduce model variance across different data splits (Ahmad & Nath, 2024). The error minimization process was optimized by reducing the Root Mean Square Error (RMSE) across training and testing datasets. The ANN model was trained using stochastic gradient descent (SGD), with an initial learning rate of 0.4 and a momentum of 0.9, balancing the speed of convergence while avoiding oscillations during weight updates (Lin & Lin, 2024).

Figure 3 illustrates the ANN model configuration, characterized by a single output neuron and multiple input neurons. By implementing these ANN configurations, this study ensures that nonlinear relationships among predictors are effectively captured, complementing the linear assumptions of PLS-SEM.

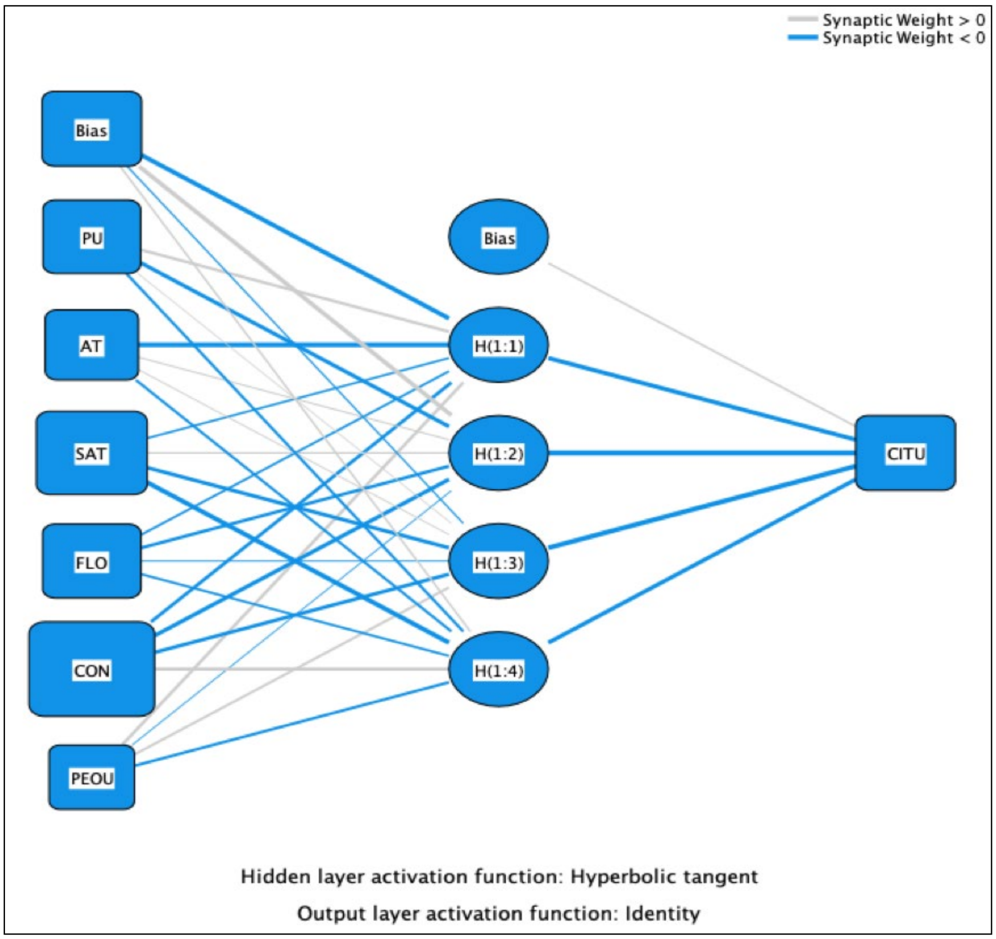

Figure 3. Artificial neural network diagram

The model's performance was further enhanced by minimizing the Root Mean Square Error (RMSE) (Xiao et al., 2023). Table 7 presents the RMSE and SSE values across the ten ANN models, along with their mean and standard deviation.

Across the ten ANN models, the mean RMSE for training was 0.110, while the mean RMSE for testing was 0.109, both of which are relatively low, indicating high predictive precision. The RMSE values account for a small proportion of the target variable's range (1-5) and approximately 3.5% of the mean of the target variable (3.089), suggesting that prediction errors remain within an acceptable range.

Furthermore, the mean Sum of Squares Error (SSE) for training was 3.634, and for testing, it was 1.567, demonstrating a consistent error reduction in the testing phase. Additionally, the standard deviation (SD) of RMSE values across the ten models was 0.0042 for training and 0.0055 for testing, indicating that the model's predictive performance remained highly consistent across different runs. The small variation in RMSE across different runs confirms that the ANN model generalizes well without significant fluctuations.

The minimal variance between training and testing results suggests the model generalizes well to unseen data, avoiding overfitting while effectively capturing key predictive factors of teachers' Continued Intention to Use (CITU) AIGC technology. Therefore, the overall low RMSE values, stable SD, and consistent SSE reduction indicate that the ANN model in this study demonstrates strong predictive performance and generalizability, reinforcing its suitability for modeling nonlinear adoption behaviors in educational settings.

Table 7. ANN model fit using RMSE values

ANN	Training			Testing			Total samples
	SSE	RMSE	N	SSE	RMSE	N	
ANN1	3.687	0.109	313	1.349	0.106	120	433
ANN2	3.847	0.115	293	1.697	0.110	140	433
ANN3	3.355	0.108	290	1.742	0.110	143	433
ANN4	3.385	0.107	296	1.967	0.120	137	433
ANN5	3.519	0.106	312	1.430	0.109	121	433
ANN6	3.265	0.105	297	1.651	0.110	136	433
ANN7	3.555	0.108	303	1.391	0.103	130	433
ANN8	3.894	0.113	305	1.714	0.116	128	433
ANN9	3.696	0.108	315	1.273	0.104	118	433
ANN10	4.136	0.118	297	1.457	0.104	136	433
Mean	3.634	0.110		1.567	0.109		
SD	0.272	0.0042		0.219	0.0055		

To further validate the predictive significance of exogenous variables in determining preschool teachers' Continued Intention to Use (CITU) AIGC technology, a sensitivity analysis was conducted using Artificial Neural Network (ANN) modeling (Arab et al., 2017). The importance of each predictor was derived from the normalized relative importance values across ten ANN models. Table 8 presents the computed mean and standard deviation (SD) of the importance scores for each exogenous variable.

The ranking of exogenous variables based on normalized relative importance highlights confirmation (CON) as the most influential factor (mean = 95.28%), followed by satisfaction (SAT) (mean = 82.41%), both of which play critical roles in shaping teachers' continued intention to use AIGC. These findings align with the Expectation-Confirmation Model (ECM), emphasizing that when teachers' expectations of AIGC are met, their satisfaction and perceived usefulness increase, ultimately fostering sustained usage.

Flow experience (FLO) (mean = 57.55%) and attitude (AT) (mean = 64.04%) exhibit moderate importance, indicating that teachers' immersion in AIGC activities and their overall attitude toward the technology significantly contribute to adoption behaviors. Meanwhile, perceived usefulness (PU) (mean = 43.18%) and perceived ease of use (PEOU) (mean = 22.35%) demonstrate the lowest importance, suggesting that while usability and usefulness perceptions matter, they are not the primary determinants of continued AIGC adoption in preschool education.

Moreover, the standard deviation (SD) values indicate stability in the ranking, with CON (SD = 7.67) and SAT (SD = 13.75) showing the least variation, confirming their strong predictive consistency across different ANN models. In contrast, FLO (SD = 22.92) and AT (SD = 18.68) exhibit higher variability, suggesting that their importance fluctuates depending on model configurations.

Overall, these findings reinforce the robustness of the ANN analysis in capturing nonlinear adoption behaviors. The ranking underscores the dominant role of confirmation and satisfaction in predicting teachers' sustained engagement with AIGC, while attitude and flow experience act as moderate influencers, and perceived ease of use remains the least significant predictor. These results reinforce the robustness of the ANN analysis in capturing nonlinear adoption behaviors, providing additional insights beyond traditional SEM-based path analysis.

Table 8. Independent variable importance

Variables	Mean importance (%)	SD (%)
CON	95.28	7.67
SAT	82.41	13.75
AT	64.04	18.68
FLO	57.55	22.92
PU	43.18	9.36
PEOU	22.35	4.91

DISCUSSION

This study aimed to investigate preschool teachers' continued intention to use Artificial Intelligence-Generated Content (AIGC) by integrating the Technology Acceptance Model (TAM), Expectation-Confirmation Model (ECM), and Flow Theory. A two-stage analytical approach using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Networks (ANNs) was applied to validate the theoretical model and enhance predictive accuracy. Eleven hypotheses were tested to examine the key determinants influencing teachers' sustained adoption of AIGC. The results confirmed that satisfaction (SAT) and attitude (AT) were the strongest predictors of continued intention to use (CITU), while confirmation (CON) and perceived usefulness (PU) played significant roles in shaping satisfaction and attitude. Additionally, flow experience (FLO) was found to positively influence both AT and CITU, highlighting the importance of engagement and immersion in shaping teachers' attitudes toward AIGC.

The findings confirm that satisfaction (SAT) significantly predicts teachers' continued use of AIGC, aligning with the Expectation-Confirmation Model (ECM), which posits that post-adoption satisfaction drives long-term technology usage (Ajibade, 2018; Yao et al., 2024). The strong impact of satisfaction on CITU ($\beta = 0.280$, $p < 0.001$) supports prior studies emphasizing the role of positive user experiences in educational technology adoption (Gajic & Boolaky, 2015; Isaac et al., 2018; Kim & Lee, 2014). Additionally, attitude (AT) emerged as a critical factor, significantly affecting CITU ($\beta = 0.262$, $p < 0.001$), consistent with TAM-based studies that highlight the influence of attitude on technology acceptance (Alfadda & Mahdi, 2021; Kelly et al., 2023; Songkram et al., 2023). The ANN analysis further corroborates these findings, ranking satisfaction (82.41%) and attitude (64.04%) as the strong influential predictors, reinforcing their essential role in shaping teachers' adoption behaviors. However, this study diverges from traditional TAM research, where perceived usefulness (PU) is often the strongest predictor of behavioral intention (Davis, 1989). The findings suggest that in the preschool education context, teachers' satisfaction and attitudes toward AIGC play a more dominant role than their perceptions of its usefulness, indicating that adoption decisions are driven more by engagement and emotional experiences rather than by efficiency alone.

Confirmation (CON) is a key determinant of satisfaction (SAT) and perceived usefulness (PU), with significant effects on PU ($\beta = 0.505$, $p < 0.001$) and SAT ($\beta = 0.349$, $p < 0.001$). This underscores the importance of meeting teachers' initial expectations and driving satisfaction with AIGC. These findings align with ECM research, which suggests that when users' initial expectations of technology are met, they develop higher satisfaction and stronger perceptions of usefulness (Mamun et al., 2020; Thong et al., 2006; Yousaf et al., 2021). This indicates that preschool teachers' continued adoption of AIGC depends on whether the technology meets their expectations regarding usability and instructional effectiveness. Previous studies in e-learning contexts have similarly shown that teachers' perceptions of technological tools improve when their initial expectations are confirmed through practical experiences (Al-Samarraie et al., 2018; Liaw & Huang, 2013). ANN results further emphasize the significance of confirmation, ranking it as the most influential predictor (95.28%), suggesting that meeting teachers' expectations is the strongest determinant of continued AIGC use. This underscores the need for institutions to provide adequate support and training to ensure that AIGC tools align with teachers' anticipated benefits, thereby enhancing satisfaction and perceived usefulness.

The role of perceived usefulness (PU) in shaping both attitude (AT) and satisfaction (SAT) further extends the applicability of TAM in the context of AIGC adoption. The results show that PU positively affects AT ($\beta = 0.530$, $p < 0.001$) and SAT ($\beta = 0.309$, $p < 0.001$), indicating that useful technologies are more likely to be adopted if they positively influence attitudes and overall satisfaction (Davis, 1989; Ofori et al., 2021; Rodríguez-Ardura & Meseguer-Artola, 2016).

However, the direct effect of PU on CITU ($\beta = 0.139$, $p < 0.05$) was weaker, indicating that its impact on continued use is largely mediated through attitude and satisfaction rather than exerting a direct influence. This finding aligns with previous studies demonstrating that perceived usefulness primarily affects adoption intention through attitudinal and experiential factors (Oematan et al., 2024; Teo & Noyes, 2011). However, this contrasts with findings in workplace technology adoption, where PU is often a direct predictor of behavioral intention (Punnoose, 2012), indicating that in educational settings, emotional and experiential factors may outweigh pure functional considerations. ANN analysis supports this interpretation, ranking PU as a moderate predictor (43.18%), reinforcing that while usefulness perceptions matter, they are only stronger than perceived ease of use in determining continued use.

Perceived ease of use (PEOU) exhibited relatively weaker direct effects on attitude ($\beta = 0.161$, $p < 0.01$) and perceived usefulness ($\beta = 0.156$, $p < 0.01$), suggesting that while usability is important, it is not the primary determinant of AIGC adoption. This aligns with the Technology Acceptance Model (TAM), which proposes that PEOU contributes to technology adoption primarily through its effect on perceived usefulness rather than as a direct driver of behavioral intention (Widiar et al., 2023). Past studies have shown that when a technology is easy to use, users are more likely to perceive it as useful, which in turn enhances their overall attitudes toward adoption (Ashraf et al., 2014; Pan, 2020; Yao et al., 2024). However, the findings of this study suggest that in the context of preschool education, ease of use plays a relatively minor role in shaping teachers' perceptions of AIGC. The ANN results confirm that PEOU is the least significant predictor (22.35%) of continued AIGC use. This finding deviates from earlier TAM research, where PEOU was a stronger determinant of adoption (Al-Adwan, 2020; Yen et al., 2010). One possible explanation is that as AI-driven educational tools become more mainstream, users prioritize effectiveness and expectation fulfillment over usability. This suggests that future AI development should focus less on interface simplicity and more on meeting pedagogical expectations and enhancing overall satisfaction.

Flow experience (FLO) was found to significantly impact both attitude (AT) ($\beta = 0.220$, $p < 0.001$) and continued use intention (CITU) ($\beta = 0.223$, $p < 0.001$), extending Flow Theory to the domain of preschool teachers' technology adoption. This theory holds the view that an immersive and engaging experience enhances intrinsic motivation and long-term behavioral commitment (Hassan et al., 2020). These results suggest that teachers who experience deep engagement and an immersive state while using AIGC are more likely to develop positive attitudes and sustain their usage. This aligns with prior studies that have emphasized the role of flow in enhancing motivation and engagement in technology use (Arghashi & Yuksel, 2022; Hoffman & Novak, 2009; Yin et al., 2023). Specifically, Arghashi and Yuksel (2022) found that flow enhances engagement, which in turn fosters stronger attitudes toward using digital technologies, a pattern also observed in this study. Similarly, Zhai et al. (2024) demonstrated that flow significantly influences long-term engagement in AI-powered learning, reinforcing the findings that engagement plays a crucial role in sustained technology adoption.

Consistent with previous studies in e-learning contexts (M.-C. Lee, 2010; Rajeh et al., 2021), this study confirms that while flow experience plays a role in shaping attitudes, its direct influence on sustained AIGC adoption is weaker than confirmation and satisfaction. However, unlike past research that primarily examined university students or general e-learning environments, this study focuses on preschool teachers within the AIGC context. The findings reinforce the expectation-confirmation perspective, highlighting that teachers' long-term use of AIGC is primarily driven by how well their expectations are met and their overall satisfaction with the technology. ANN results further support this, ranking flow experience as moderately important (57.55%), significantly lower than confirmation (95.28%) and satisfaction (82.41%). This suggests that while an engaging AIGC experience fosters positive attitudes, sustained adoption depends more on aligning with teachers' expectations and ensuring overall satisfaction. These insights provide valuable guidance for AIGC developers and educators seeking to design more effective and sustainable implementations.

In this study, PLS-SEM identifies direct causal relationships, and ANN highlights the relative importance of each predictor. Notably, while PLS-SEM identified SAT as the strongest predictor of CITU, ANN analysis ranked CON as the most influential factor (95.28%), surpassing SAT (82.41%). This suggests that while satisfaction directly drives continued usage in a linear model, confirmation plays a more intricate role in influencing both satisfaction and usefulness, which in turn shape attitudes and behavioral intentions. By integrating PLS-SEM and ANN, this study advances technology adoption research by revealing that expectation fulfillment (CON) outweighs usability considerations (PEOU) and perceived functionality (PU) in predicting sustained AIGC adoption. While PLS-SEM establishes direct causal effects, ANN's nonlinear approach highlights that CON has a stronger predictive impact (95.28%) than previously assumed in linear models, underscoring its fundamental role in shaping satisfaction and long-term adoption. Unlike previous studies that emphasized PU as the dominant factor (Davis, 1989; Prayoga & Abraham, 2016; Teo et al., 2009), the findings of this study highlight that expectation fulfillment and satisfaction are the key drivers in AI-based educational environments. This shift in determinants underscores the need for AI developers and policymakers to focus on aligning AI tools with user expectations to enhance adoption outcomes.

CONCLUSION

This study provides a comprehensive analysis of the key factors influencing preschool teachers' sustained use of Artificial Intelligence-Generated Content (AIGC) in educational settings. By integrating the Technology Acceptance Model (TAM), Expectation-Confirmation Model (ECM), and Flow Theory, this study presents a holistic framework that captures cognitive, affective, and experiential determinants of continued AIGC adoption, extending prior research that primarily focused on initial adoption.

Using Partial Least Squares-Structural Equation Modeling (PLS-SEM), this study tested the relationships among key adoption factors, while Artificial Neural Networks (ANN) provided a deeper understanding of the relative importance of each predictor. The results confirm that satisfaction ($\beta = 0.280$, $p < 0.001$) and attitude ($\beta = 0.262$, $p < 0.001$) are the strongest predictors of continued use, reinforcing the importance of ensuring a positive user experience in educational AI adoption. Expectation confirmation ($\beta = 0.505$, $p < 0.001$) significantly enhances both perceived usefulness and satisfaction, suggesting that meeting teachers' expectations is critical for sustaining AIGC adoption. Flow experience ($\beta = 0.223$, $p < 0.001$) positively impacts attitude and continued use, but its direct effect is weaker compared to confirmation and satisfaction, indicating that engagement alone is not sufficient for long-term adoption. ANN analysis further ranks confirmation (95.28%) and satisfaction (82.41%) as the most influential factors, whereas perceived ease of use (22.35%) has a relatively minor impact. These findings challenge the traditional TAM assumption that perceived usefulness is the primary determinant of technology adoption (Choi et al., 2023). Instead, this study demonstrates that sustained AIGC use among preschool teachers is more strongly influenced by expectation confirmation and satisfaction, highlighting the importance of aligning AIGC tools with educators' needs and experiences.

IMPLICATIONS

THEORETICAL IMPLICATION

This study advances knowledge in the field of AI-driven educational technology by addressing the sustained adoption of Artificial Intelligence-Generated Content (AIGC) among preschool teachers, an area that has received limited attention in prior research. While most existing studies focus on initial adoption and the role of perceived usefulness (PU) and perceived ease of use (PEOU) in technology acceptance, this study highlights the long-term determinants of AIGC use, particularly expectation confirmation, satisfaction, and flow experience.

By integrating TAM, ECM, and Flow Theory, this study extends traditional technology adoption frameworks by demonstrating that cognitive (PU, PEOU), affective (satisfaction, attitude), and experiential (flow experience, confirmation) factors work together to drive sustained technology use. Unlike previous research, which either assumes that both PU and PEOU must be high for continued adoption or that PU alone is sufficient, this study reveals that expectation confirmation and satisfaction outweigh ease of use in predicting long-term adoption behavior.

Furthermore, the application of Artificial Neural Networks (ANN) alongside PLS-SEM provides a novel methodological contribution, allowing for the identification of non-linear interactions that traditional statistical models might overlook. While PLS-SEM establishes direct causal pathways, ANN highlights the relative importance of predictors, reinforcing the need to combine linear and nonlinear analytical methods in technology adoption research (Leong et al., 2024). The ANN results confirm that confirmation (95.28%) and satisfaction (82.41%) are the most influential predictors, challenging prior assumptions that perceived usefulness alone determines long-term adoption. These insights provide a more comprehensive foundation for designing teacher-centered AI solutions that align with user expectations, ensuring long-term engagement and meaningful pedagogical integration.

PRACTICAL IMPLICATION

The findings offer valuable insights for educators, policymakers, and AI developers in enhancing the adoption and long-term use of AIGC in preschool education.

For educators, the results suggest that professional training programs should be designed to ensure that AIGC tools align with pedagogical needs, emphasizing instructional effectiveness rather than merely improving usability. Providing real-time feedback mechanisms, AI-powered personalized content, and interactive digital environments can enhance engagement and satisfaction, leading to sustained adoption.

For policymakers, the findings highlight the need to establish comprehensive guidelines for AIGC implementation in early childhood education. Policies should prioritize technical support, continuous training, and funding mechanisms to ensure teachers receive adequate institutional backing. Governments and educational institutions should also invest in research to explore the long-term effects of AI-based learning tools on preschool education outcomes.

For AI developers, the results emphasize that enhancing expectation fulfillment and satisfaction is more critical than merely improving system usability. Developers should focus on gamification elements, adaptive learning features, and immersive engagement tools that foster deeper teacher interaction with AI-driven content. Given that ANN results ranked confirmation (CON) as the most significant predictor, developers should prioritize creating AI-driven tools that meet teachers' expectations of instructional effectiveness and usability, ensuring higher engagement and long-term adoption.

LIMITATIONS AND FUTURE RESEARCH

Despite its contributions, this study has several limitations. First, the sample was limited to preschool teachers, which may restrict the generalizability of the findings to other educational contexts. Future research should examine AIGC adoption across primary, secondary, and higher education levels to assess whether similar predictors influence continued use. Second, this study relied on self-reported data, which may introduce potential bias (Rosenman et al., 2011). Future studies could complement survey data with objective behavioral measures, such as system log data, to validate the reported findings. Third, while this study employed ANN to enhance predictive accuracy, other machine learning techniques, such as deep learning models, could provide further insights into the complexity of AIGC adoption. Lastly, this study focused on psychological and attitudinal determinants without incorporating external institutional factors such as administrative support, policy regulations, and ethical concerns, which may also shape sustained AIGC adoption. Future studies should examine how policy frameworks, government initiatives, and ethical considerations influence long-term AI integration in education.

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