DOI Link: https://doi.org/10.59671/xi0R9
Vol.408, Issue.5, Part.1, May 2025, PP.168-207

Factors Influencing Preschool Teachers' Continuous Intention to Use AIGC in Education

Zhang Yuxin (Lorraine)
Universiti Malaya, Department of Curriculum and Instructional Technology
ORCID: 0009-0000-0893-6848

Email: yuxin.922@outlook.com; Official email: 22104805@siswa.um.edu.my

Abstract

Artificial Intelligence Generated Content (AIGC) is becoming a valuable tool in education. It supports personalized, interactive, and scalable learning. However, little is known about how preschool teachers continue using AIGC in their daily practice. This study explores the key factors that influence their sustained intention to use AIGC technologies. It integrates three theoretical models—Technology Acceptance Model (TAM), Expectation Confirmation Model (ECM), and Flow Theory—into a unified framework. Data were collected through a questionnaire survey of preschool teachers in China. The results were analyzed using both Partial Least Squares Structural Equation Modeling (PLS-SEM) and Fuzzy Set Qualitative Comparative Analysis (fsQCA). Findings show that confirmation and perceived usefulness are strong predictors of continuous use. In contrast, perceived ease of use plays a smaller role. The fsQCA results also reveal three distinct combinations of conditions that lead to high usage intention. These findings provide new insights into teacher technology adoption and offer practical guidance for promoting sustainable use of AIGC in early childhood education, especially in developing regions.

Keywords: Preschool teachers; Continuous intention to use; AIGC; Education; Pls-sem; fsQCA

1. INTRODUCTION

Artificial Intelligence Generated Content (AIGC) is an emerging technology that enables the automatic creation of learning materials such as text, images, audio, and video. It relies on advanced techniques including Natural Language Processing (NLP), Computer Vision (CV), and deep learning (Jin et al., 2024). In the field of education, AIGC offers tools to support personalized, scalable, and interactive learning environments (J. Guo et al., 2024). Well-known platforms such as Khan Academy, Duolingo, and QuillBot have begun using AIGC to provide adaptive learning content and feedback (DiCerbo, 2021; Amyatun & Kholis, 2023; Vega et al., 2024). These applications are made possible by improvements in cloud computing, high-speed networks, and AI processing power (Liang et al., 2024).

Beyond general applications, researchers have also examined AIGC's specific benefits for teaching and learning. Recent studies show that AIGC can reduce teachers' preparation workload and support students through personalized and interactive content (Lu et al., 2024). It also allows students to explore content more independently and creatively (Guo et al., 2024). In addition, AIGC has been used to support intelligent tutoring systems, personalized curricula, and immersive learning environments (Huang et al., 2024; Lu et al., 2024).

Despite its potential, AIGC remains underused in early childhood education. Most existing studies focus on higher education (Sharma & Srivastava, 2020) or vocational settings (Antonietti et al., 2022), which differ significantly from preschool environments in terms of learners' developmental needs and teaching strategies. Preschool teachers often face distinct challenges when adopting emerging technologies. These include limited access to technical infrastructure, inadequate support platforms, and insufficient training tailored to early learning contexts (Dai et al., 2023). Scholars have also raised concerns about ethical and privacy issues when AIGC is used with young children (Ma et al., 2024). These barriers may reduce preschool teachers' willingness to adopt AIGC, especially in the long term. Understanding what influences their continuous use of AIGC is therefore critical for its successful implementation in preschool settings.

To explore this issue, the study draws on three theoretical models commonly used in educational technology research: The Technology Acceptance Model (TAM), the Expectation Confirmation Model (ECM), and Flow Theory. TAM focuses on perceived usefulness and ease of use as key predictors of adoption (Davis, 1989). ECM explains users' continued intention through satisfaction and expectation alignment (Bhattacherjee, 2001). Flow theory adds an emotional dimension by capturing the immersive and enjoyable experience of technology use, which may be especially relevant in preschool settings (Csikszentmihalyi, 1990). While some studies have combined TAM and ECM in the context of online and mobile learning (Al-Nuaimi & Al-Emran, 2021), few have included Flow Theory, and even fewer have applied all three in combination to study AIGC adoption in early childhood education.

In addition to theoretical integration, this study also adopts a dual-method approach to analyze data. This study applied Partial Least Squares Structural Equation Modeling (PLS-SEM) and Fuzzy Set Qualitative Comparative Analysis (fsQCA). PLS-SEM helps to find linear relationships between variables, while fsQCA provides a configurational perspective that reveals multiple causal pathways (Al-Rahmi et al., 2022; Zheng et al., 2023). This combination helps capture both dominant and alternative configurations of influencing factors,

ISSN: 0034-8082

reflecting the complexity of technology adoption in preschool contexts. Therefore, the purpose of this study is to investigate the behavioral, cognitive, and emotional determinants of preschool teachers' continuous intention to use AIGC technologies. It aims to answer two questions: (1) What factors influence preschool teachers' continuous intention to use AIGC? and (2) How do these factors interact to shape different patterns of continued use?

2. THEORETICAL BACKGROUND

This study integrates three established models—the Expectation Confirmation Model (ECM), Technology Acceptance Model (TAM), and Flow Theory—to examine preschool teachers' continuous intention to use AIGC. Each model contributes a unique perspective: ECM explains satisfaction-based post-use behavior, TAM addresses rational acceptance, and Flow Theory incorporates emotional immersion. Together, they provide a comprehensive understanding of sustained technology use in early childhood education.

2.1 Expectation Confirmation Model

Originally used in consumer behavior research, ECM has been widely applied to study users' post-adoption behavior in information systems (Xia & Chae, 2021). It suggests that when users' actual experience with a system matches or exceeds their initial expectations, they feel satisfied, which reinforces their intention to continue using the system (Vafaei-Zadeh et al., 2024). In educational contexts, studies show that confirmation enhances both perceived usefulness and satisfaction (Deng et al., 2010; Hashim et al., 2023). For teachers using AIGC, confirmation may reflect the extent to which these tools meet pedagogical needs and improve classroom efficiency. Therefore, ECM helps explain how experience shapes long-term attitudes toward AIGC in real teaching environments.

2.2 Technology Acceptance Model

TAM is a foundational model for predicting user adoption of technology, emphasizing perceived usefulness (PU) and perceived ease of use (PEOU) as core predictors (Davis, 1989). In education, numerous studies have validated TAM in various settings—from e-learning platforms to AI-driven tutoring systems—highlighting its adaptability (Shiau & Chau, 2016; Xiong et al., 2024). PU reflects teachers' beliefs about how AIGC enhances teaching quality or reduces workload, while PEOU captures how simple the system is to learn and use. Some scholars have extended TAM by integrating emotional and contextual variables, especially in settings involving complex users like older adults or low-tech users (Wu & Chen, 2017; Eraslan Yalcin & Kutlu, 2019). In preschool contexts, where many teachers have limited exposure to AI tools, these constructs are particularly important.

2.3 The Flow Theory

Flow Theory addresses users' emotional and motivational states when interacting with a system. Flow occurs when users are deeply focused, enjoy the experience, and feel a sense of control (Michailidis et al., 2018). In education, flow is often used to explain engagement and satisfaction in immersive learning environments, such as gamified platforms or intelligent tutoring systems (Chiu & Chen, 2023; Yang, 2024). For preschool teachers, the flow may emerge when they find AIGC tools both engaging and useful in designing creative lessons. Studies suggest that flow not only enhances enjoyment but also increases positive attitudes and behavioral intentions (Hoffman & Novak, 2009). Thus, flow bridges cognitive effort and emotional commitment, offering a complementary perspective to TAM and ECM.

ISSN: 0034-8082

2.4 Model Conceptualization and Hypotheses Development

This study proposes an integrated framework that combines the Expectation Confirmation Model (ECM), Technology Acceptance Model (TAM), and Flow Theory to explain preschool teachers’ continuous use of AIGC. ECM highlights how teachers' experiences with AIGC—when aligned with their initial expectations—can increase their satisfaction and perceived value of the technology. TAM captures the cognitive evaluations of usefulness and ease of use that shape attitudes and behavioral intentions. Flow Theory adds an emotional dimension, emphasizing the role of enjoyment and deep engagement in shaping sustained use. By integrating these three models, the framework offers a comprehensive view that includes post-use evaluation, rational judgment, and emotional immersion—key elements for understanding long-term technology adoption in early childhood education.

2.5 Confirmation

Confirmation reflects the extent to which teachers feel AIGC tools meet their initial expectations. It strengthens both their belief in the tool’s value and their emotional satisfaction.

- H1: Confirmation (CON) positively influences preschool teachers’ perceived usefulness (PU).
- H2: Confirmation (CON) positively influences preschool teachers’ satisfaction (SAT).

2.6 Flow theory

Flow represents the psychological state of full immersion and enjoyment. When teachers experience flow while using AIGC, they are more likely to develop favorable attitudes and intentions to keep using the tool.

- H3: Flow experience (FLO) positively influences preschool teachers' continuous intention to use (CITU).
- H4: Flow experience (FLO) positively influences preschool teachers' attitudes (AT).

2.7 Attitude

Attitude reflects teachers' overall evaluation of AIGC use. A positive attitude builds trust and encourages sustained use behavior.

- H5: Attitude (AT) positively influences preschool teachers' continuous intention to use (CITU).

2.8 Perceived Usefulness and Perceived Ease of Use

PU influences both teachers' attitudes toward AIGC and their intention to keep using it. PEOU shapes PU and attitude by making the technology easier to learn and apply in classroom settings.

- H6: Perceived ease of use (PEOU) positively influences preschool teachers' attitude (AT).
- H7: Perceived ease of use (PEOU) positively influences preschool teachers' perceived usefulness (PU).
- H8: Perceived usefulness (PU) positively influences preschool teachers' continuous intention to use (CITU).
- H9: Perceived usefulness (PU) positively influences preschool teachers' attitude (AT).

- H10: Perceived usefulness (PU) positively influences preschool teachers' satisfaction (SAT).

2.9 Satisfaction

Satisfaction is the positive emotional response to using AIGC tools. It reinforces trust and increases teachers' willingness to continue use.

- H11: Satisfaction (SAT) positively influences preschool teachers' continuance intention to use (CITU).

3. METHODOLOGY

3.1 Sample Selection and Collection

This study adopted a quantitative approach using a questionnaire survey. The target participants were preschool teachers across different regions of China who had basic digital literacy and were familiar with AIGC technology. Participation was entirely voluntary for all respondents. The questionnaire was distributed via Google Forms, and data were collected online. To ensure sample representativeness and data quality, purposive sampling was applied. A power analysis using G*Power determined that a minimum of 146 responses were needed, based on an effect size of 0.15, significance level of 0.05, statistical power of 0.95, and number of predictors of 6. In total, 433 valid questionnaires were collected, providing statistical support for data analysis and interpretation. The sample included 59.8% female and 40.1% male participants, with ages ranging from 20 to over 50, covering various career stages. The demographic profile is shown in Table 1.

Table 1. Profile of respondents

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

3.2 Instrument

This study used a questionnaire survey to assess preschool teachers' intentions to use AIGC technology in education and the influencing factors. The questionnaire consisted of two sections. The first section collected demographic information such as age, gender, and educational background. The second section measured the study's constructs—Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Satisfaction (SAT), Continuance Intention to Use (CITU), Flow Experience (FLO), Confirmation (CON), and Attitude (AT)—using a 5-point Likert scale ranging from "strongly disagree" to "strongly agree".

All items were adapted from validated scales in previous research. PEOU and PU were based on Davis et al., (1989), while AT items came from Teo et al., (2009). FLO was adapted from Jackson and Marsh (1996). Items for CON and CITU were drawn from Bhattacherjee (2001), and SAT was measured using items from

Spreng and Olshavsky (1993). These scales have demonstrated strong reliability and validity in prior educational technology studies.

3.3 Data Analysis

Data were analyzed using a dual-method approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM) and Fuzzy Set Qualitative Comparative Analysis (fsQCA). PLS-SEM was conducted using SmartPLS to test the proposed model's measurement and structural components. Reliability and validity of constructs were assessed, followed by path analysis to evaluate the strength and significance of relationships between variables. To complement this, fsQCA was used to identify combinations of factors that jointly influence continuance intention. Unlike PLS-SEM, which assumes linear and symmetric relationships, fsQCA explores causal complexity by identifying multiple configurations that lead to the same outcome (Ho et al., 2016; Kaya et al., 2020). This study combines PLS-SEM and fsQCA to explore both linear effects and causal complexity. While PLS-SEM shows which variables individually predict continued use, fsQCA reveals how different configurations of factors jointly lead to high continuance intention.

4. FINDINGS

4.1 Symmetric Analysis

4.1.1 Measurement model assessment

According to Sarstedt et al., (2014), the outer model needs to be tested when building the model. The main indicators for assessing the outer model are Composite Reliability (CR), factor loadings, and Average Variance Extracted (AVE). In this study, all outer loadings are above the recommended value of 0.7, CR is above 0.8, and AVE exceeds 0.5, meeting the standard requirements

(Purwanto & Sudargini, 2021). The specific values for loadings, CR, and AVE are shown in Table 2.

Table 2. Measurement model assessment

Constructs	Items	Loadings	CR	AVE
Perceived ease of use	PEOU1	0.895	0.896	0.742
	PEOU2	0.840		
	PEOU3	0.847		
Perceived usefulness	PU1	0.857	0.895	0.739
	PU2	0.840		
	PU3	0.881		
Attitude	AT1	0.884	0.915	0.781
	AT2	0.897		
	AT3	0.871		
Satisfaction to use	SAT1	0.922	0.944	0.850
	SAT2	0.924		
	SAT3	0.920		
Continuance intention to use	CITU1	0.901	0.935	0.828
	CITU2	0.907		
	CITU3	0.922		
Flow experience	FLO1	0.795	0.894	0.739
	FLO2	0.911		
	FLO3	0.868		
Confirmation	CON1	0.923	0.938	0.835
	CON2	0.899		
	CON3	0.920		

ISSN: 0034-8082

According to Henseler et al., (2015), the HTMT method was used to further assess discriminant validity. Therefore, this study applied the approach to test discriminant validity. As shown in Table 3, all HTMT values are below the threshold of 0.85, indicating no issues with discriminant validity among the constructs.

Table 3. Discriminant validity

Discriminant validity (HTMT)							
	CITU	FLO	AT	AT	PEOU	PU	SAT
CITU							
CON	0.719						
FLO	0.589	0.581					
AT	0.684	0.724	0.467				
PEOU	0.198	0.355	0.092	0.409			
PU	0.621	0.640	0.413	0.784	0.375		
SAT	0.669	0.573	0.560	0.623	0.202	0.579	

4.1.2 Structural model assessment

For R^2, the highest value is 1, indicating complete explanation, while the lowest is 0. According to Cheah et al., (2018), R^2 values of 0.26, 0.13, and 0.02 represent significant, moderate, and weak explanatory power, respectively. As shown in Table 4, the R^2 values of the endogenous variables in this study, reflect the model’s predictive capability.

In this study, the R^2 value of continuous intention to use (CITU) indicates that the predictors in the model explain approximately 51.8% of the variance in continued

ISSN: 0034-8082

use intention, demonstrating strong explanatory power. The R^2 value of attitude (AT) is 0.500, further confirming the model's strong predictive power for this variable. Additionally, the R^2 values for perceived usefulness (PU) and satisfaction (SAT) also indicate significant explanatory power.

Table 4. Coefficient of determination

Endogenous variables	R square
CITU	0.518
AT	0.500
PU	0.328
SAT	0.336

Before evaluating the structural model, a collinearity test is required to ensure that collinearity does not bias the regression results (Dormann et al., 2013). The Variance Inflation Factor (VIF) is calculated using the latent variable scores of predictor structures in partial regression. High correlations between two or more predictors may cause multicollinearity, leading to redundant information in the model. Lower VIF values indicate less correlation between variables. If VIF values are below 3.3, the model is generally considered free from severe multicollinearity (Kock, 2015).

In this study's model, all latent variables underwent VIF testing, and the results showed that all VIF values were below 3.3 (see Table 5). Therefore, it can be confirmed that there are no multicollinearity issues in the structural model of this study.

Table 5. VIF results

Variables	Items	VIF
	CITU1	2.511
CITU	CITU2	2.735
	CITU3	3.076
	CON1	3.098
CON	CON2	2.516
	CON3	3.042
	FLO1	2.225
FLO	FLO2	2.977
	FLO3	1.711
	AT1	2.062
AT	AT2	2.426
	AT3	2.149
	PEOU1	2.185
PEOU	PEOU2	1.892
	PEOU3	1.727
	PU1	1.836
PU	PU2	1.767
	PU3	2.008
	SAT1	3.134
SAT	SAT2	3.224
	SAT3	2.953

To examine the path coefficients in the proposed model, this study used a bootstrap method to estimate t-values and determine path significance (Streukens & Leroi-Werelds, 2016). Path coefficient values range from -1 to +1, with values closer to +1 indicating a stronger positive relationship, and values closer to -1 indicating a stronger negative relationship. Therefore, the significance level for path coefficients was set at 0.05.

As shown in Table 6, all hypotheses proposed in this study are supported, indicating the overall validity of the model. Specifically, path coefficient analysis reveals that confirmation (CON) has a significant positive effect on perceived usefulness (PU) ($\beta = 0.505$, $p < 0.01$) and satisfaction (SAT) ($\beta = 0.349$, $p < 0.01$), showing that preschool teachers' sense of confirmation can significantly enhance their perception of AIGC's usefulness and satisfaction. Additionally, flow experience (FLO) significantly impacts continued use intention (CITU) ($\beta = 0.223$, $p < 0.01$) and attitude (AT) ($\beta = 0.220$, $p < 0.01$), highlighting the important role of immersion in promoting continued use intentions.

The model results further indicate a positive effect of attitude (AT) on continuous intention to use (CITU) ($\beta = 0.262$, $p < 0.01$), a significant positive effect of perceived ease of use (PEOU) on attitude (AT) ($\beta = 0.161$, $p < 0.01$) and perceived usefulness (PU) ($\beta = 0.156$, $p < 0.01$), and a significant effect of perceived usefulness (PU) on continuous intention to use (CITU) ($\beta = 0.139$, $p < 0.01$). Besides, perceived usefulness (PU) also positively influences attitude (AT) ($\beta = 0.530$, $p < 0.01$) and satisfaction (SAT) ($\beta = 0.309$, $p < 0.01$), suggesting that perceived usefulness not only strengthens preschool teachers' attitudes toward using AIGC in education but also increases satisfaction. Finally, satisfaction (SAT) has a significant positive effect on continuous intention to use (CITU) ($\beta = 0.280$, $p < 0.01$).

Effect sizes were classified according to Cohen's standards as small (0.02), medium (0.15), and large (0.35) (Lorah, 2018). According to the results, perceived usefulness (PU)'s effect on attitude (AT) and confirmation (CON)'s effect on perceived usefulness (PU) are large, while perceived ease of usefulness (PEOU)'s effect on attitude (AT) and perceived usefulness (PU), as well as perceived usefulness (PU)'s effect on continuous intention to use (CITU), are small. The remaining paths show medium effects.

Table 6. Results of hypotheses testing

	Relationships	Path coefficients	T values	P values	F^2	Effect size	Decision
H1	CON→PU	0.505	10.935	0.000	0.343	Large	Supported
H2	CON→SAT	0.349	6.341	0.000	0.128	Medium	Supported
H3	FLO→CITU	0.223	5.196	0.000	0.075	Medium	Supported
H4	FLO→AT	0.220	5.559	0.000	0.084	Medium	Supported
H5	AT→CITU	0.262	4.457	0.000	0.069	Medium	Supported
H6	PEOU→AT	0.161	4.405	0.000	0.047	Small	Supported
H7	PEOU→PU	0.156	3.507	0.000	0.033	Small	Supported
H8	PU→CITU	0.139	2.610	0.009	0.021	Small	Supported
H9	PU→AT	0.530	12.652	0.000	0.442	Large	Supported
H10	PU→SAT	0.309	5.708	0.000	0.100	Medium	Supported
H11	SAT→CITU	0.280	5.457	0.000	0.096	Medium	Supported

To assess model quality, this study evaluated model fit using the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). An SRMR value below 0.08 indicates a good model fit, calculated by subtracting the model-implied correlation matrix from the observed correlation matrix (Molwus

ISSN: 0034-8082

et al., 2013). Shi and Maydeu-Olivares (2020) proposed SRMR as a measure for assessing model fit in PLS-SEM to prevent model misspecification. The NFI is used to compare the chi-square value of the proposed model with that of a baseline model, where an NFI value above 0.8 is generally acceptable (Ramlall, 2016).

Table 7. Testing model fit

Parameter	Saturated model	Estimated model
SRMR	0.053	0.080
NFI	0.839	0.834

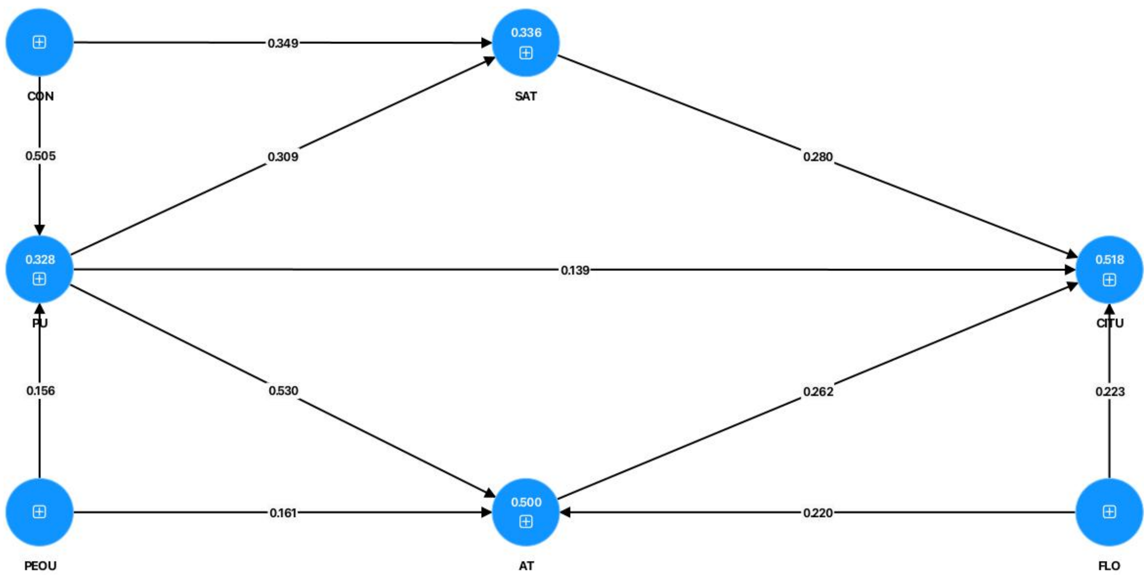

Figure 1. The research model (symmetric model)

In this study, the SRMR value for the saturated (measurement) model is 0.053, which is below the 0.08 standard. Meanwhile, the SRMR value for the structural (estimated) model is 0.080, which is within the acceptable range. For the NFI, the saturated model shows an NFI of 0.839, and the estimated model shows an NFI of 0.834, both reaching the 0.8 threshold, indicating an acceptable model fit. The

ISSN: 0034-8082

model fit and test results are illustrated in the final research model shown in Table 7 and Figure 1.

4.2 Asymmetric analysis

To analyze from different perspectives, this study used the fsQCA method. PLS-SEM is based on symmetrical assumptions and aims to explore the net effects between variables in the model, while fsQCA examines the complex and asymmetrical relationships between causal factors and outcomes, generating multiple pathways (Kline, 2012; Rasoolimanesh et al., 2021). FsQCA supports both inductive and deductive reasoning, making it well-suited for testing, constructing, and interpreting theories by revealing how multiple combinations of conditions affect the outcome variable (Salonen et al., 2021). Given the complex causal relationship patterns between independent and dependent variables in this study, using fsQCA allows for a more comprehensive understanding of the underlying causes, uncovering hidden relationships.

4.2.1 Calibration

In this study, calibration was the initial stage of the fsQCA analysis, following the standard procedure outlined by Ragin and Fiss (2008). To convert ordinal scale data into fuzzy set membership scores, this study used the calibration function in fsQCA 4.0 to transform the variable scores from the PLS-SEM into fuzzy set scores. On the fuzzy set scale, scores range from 0 to 1, where 0 indicates full non-membership, 1 indicates full membership, and 0.5 serves as the threshold for the cross-over point (or intermediate set) (Burrough, 1989). Given that this study used a 5-point Likert scale, the three key calibration thresholds were set at 5 (full membership), 3.5 (cross-over point), and 1 (non-membership) (Zhang et al., 2022).

4.2.2 Configurations

According to Dul, (2016), a necessity analysis should be conducted first. After analyzing each potential causal condition, this study found that the highest consistency was around 0.91, slightly above the necessity threshold of 0.90. Thus, perceived ease of use (PEOU), perceived usefulness (PU), and attitude (AT) were identified as necessary conditions for high continuous intention to use (CITU) among preschool teachers, while ~FLO was a necessary condition for low CITU.

Then, a truth table was generated using fsQCA 4.0. Following Pappas et al., (2020), a frequency threshold of 3 was applied. For smaller samples (around 100), a frequency threshold of 2 is appropriate, while for larger samples (>150), a threshold of 3 or higher is recommended. The results of the necessary conditions for CITU are in Table 8.

Table 8. Analysis of necessary condition for CITU

	High CITU		Low CITU	
Antecedents	Consistency	Coverage	Consistency	Coverage
PEOU	0.903	0.621	0.784	0.711
~PEOU	0.579	0.670	0.582	0.888
PU	0.911	0.701	0.680	0.692
~PU	0.600	0.587	0.707	0.913
AT	0.914	0.740	0.642	0.686
~AT	0.612	0.564	0.757	0.921
SAT	0.782	0.845	0.500	0.712
~SAT	0.733	0.526	0.891	0.844
FLO	0.690	0.860	0.443	0.729
~FLO	0.782	0.516	0.914	0.795
CON	0.896	0.797	0.575	0.675
~CON	0.634	0.531	0.827	0.913

ISSN: 0034-8082

In fsQCA analysis, the three main solution types are the parsimonious solution, complex solution, and intermediate solution. This study chose the intermediate solution due to its advantages in interpretability and model completeness (Chuah et al., 2021). The results indicate that three distinct configurations can lead to high continuous use intention (CITU). When interpreting fsQCA results, consistency and coverage are two key criteria for evaluating the model. Consistency measures the accuracy of a configuration in predicting the outcome, while coverage assesses the importance of the configuration in explaining the outcome. In this study, each configuration shows high levels of consistency (>0.90) and raw coverage (>0.50). Specifically, the overall consistency of the three configurations is 0.918, and the coverage is 0.764, indicating that these configurations sufficiently explain the observed results (see Table 9).

Table 9. Sufficient configurations for CITU

	CITU		
Configuration	Path 1	Path 2	Path 3
PEOU			●
PU	●	●	
AT	●	●	●
SAT	●		●
FLO		●	●
CON	●	●	●
Consistency	0.933	0.945	0.967
Raw coverage	0.705	0.632	0.573
Unique coverage	0.122	0.049	0.009
Overall consistency		0.918	
Overall coverage		0.764	

ISSN: 0034-8082

Note: ●denotes the presence of a condition, ●denotes the marginal presence of a condition. Blank spaces indicate the condition may be either present or absent.

Raw coverage = outcome share explained by a configuration, unique coverage = outcome share exclusively explained by a configuration.

5. DISCUSSION

This study aimed to identify the determinants influencing preschool teachers' continuous intention to use AIGC technologies by integrating the Technology Acceptance Model (TAM), the Expectation Confirmation Model (ECM), and Flow Theory. Using both PLS-SEM and fsQCA, the study explored linear relationships and configurational patterns among key cognitive and affective constructs. The findings emphasize the significance of perceived usefulness, perceived ease of use, confirmation, flow experience, satisfaction, and attitude in shaping teachers' continued use of AIGC, while also revealing diverse causal configurations.

PLS-SEM analysis revealed that confirmation (CON) plays a central role in influencing both perceived usefulness and satisfaction. This is in line with the ECM framework (Bhattacherjee, 2001), which posits that users' post-adoption experiences—particularly whether their initial expectations are met—significantly influence ongoing usage decisions. In the context of preschool education, confirmation reflects whether teachers perceive that AIGC tools are as effective as anticipated. This finding is consistent with Khan and Saleh (2023), Rahi et al., (2023), and Thong et al., (2006), who also highlighted confirmation as a key determinant of satisfaction and continued use. Notably, confirmation had a stronger effect on perceived usefulness than perceived ease of use, suggesting that practical alignment with expectations matters more than initial simplicity.

ISSN: 0034-8082

Perceived usefulness (PU) emerged as another central factor, influencing satisfaction, attitude, and continued use intention. This finding supports the foundational logic of TAM (Davis et al., 1989), wherein users' belief that technology improves task performance leads to favorable attitudes and behavioral intentions. Teachers who view AIGC tools as helpful in managing classroom activities or tailoring instruction are more likely to adopt them over the long term. As Cullen and Greene (2011) also suggested, when educators perceive that a system enhances their performance, their motivation to integrate it increases significantly. This result also mirrors findings from Runhaar (2017) in related education contexts, but its confirmation in early childhood education adds novelty to the literature.

Although perceived ease of use (PEOU) had a smaller effect size, its indirect influence through PU and attitude remains important. Previous research has shown that while ease of use may not directly impact long-term intention, it plays a critical role in the early stages of technology adoption (Alshammari & Babu, 2025; Hamid et al., 2016). In this study, the indirect effect of PEOU suggests that simplifying interfaces and reducing operational barriers remain important to promote initial engagement. This is particularly relevant for preschool teachers, who may have less access to professional digital training. In preschool education, where teachers may not always be tech-savvy, the simplicity and intuitiveness of AIGC tools can lower adoption barriers and facilitate initial engagement (Barbuto et al., 2003; Brito & Dias, 2017). This confirms earlier findings by Svetsky and Moravcik (2019), who found that reducing technological friction improves user experience and long-term viability.

ISSN: 0034-8082

Flow experience (FLO) was found to significantly influence both attitude and continuance intention, confirming the role of emotional engagement in technology use. According to Flow Theory, when users are immersed in a task and find it intrinsically enjoyable, their commitment deepens (Guo et al., 2012). This study demonstrates that teachers who experienced flow during their interaction with AIGC tools—such as feeling focused, creative, and in control—were more likely to view the technology positively and continue using it. This aligns with Tseng et al., (2022), who argued that emotional engagement significantly enhances technology adoption in education. Moreover, this emotional pathway provides a complementary lens to the emphasis of TAM and ECM suggesting that affective involvement is as crucial as cognitive evaluation in shaping long-term behavior.

Attitude (AT) was another significant predictor of continuance intention, influenced directly by PU, PEOU, and flow experience. This reaffirms TAM's notion that favorable user attitudes mediate between beliefs and behavior (Kim et al., 2009; López-Bonilla & López-Bonilla, 2017). The particularly strong path from PU to attitude indicates that instrumental beliefs are critical, while flow contributes to attitudinal shifts by increasing emotional involvement. This dual pathway highlights the value of combining cognitive and experiential perspectives to understand user behavior, particularly in emotionally rich settings like preschool education.

Satisfaction (SAT) played a mediating role in the model, influenced by both confirmation and perceived usefulness. The path analysis showed moderate and significant effects, indicating that teachers' satisfaction is shaped by both their initial expectations and the practical utility of AIGC tools. This aligns with Philip and Soo-Young (2013) and Spreng and Olshavsky (1993), who emphasized that

ISSN: 0034-8082

satisfaction results from the comparison between expectations and perceived performance. In the context of preschool education, confirmation reassures teachers that AIGC meets their anticipated instructional value, while perceived usefulness reinforces the belief that the tools enhance teaching effectiveness. Together, these factors contribute to a sense of contentment and confidence, which in turn strengthens teachers' commitment to continued use. The dual influence of cognitive evaluation and expectation alignment on satisfaction is consistent with findings by Chen (2011) and Wu et al., (2010), who demonstrated that satisfaction is not only an emotional response but also an indicator of perceived system reliability and pedagogical compatibility. Given its significant direct impact on continuance intention, satisfaction emerges as a critical construct linking both rational judgment and emotional assurance.

The fsQCA analysis provided additional insights beyond those uncovered by PLS-SEM. Three configurations were identified as sufficient for high continuance intention. The first path, characterized by attitude, satisfaction, and confirmation as core conditions, suggests that positive affect and validated expectations can drive sustained usage even when perceived usefulness is only peripheral. This finding supports Li et al., (2024), who highlighted the role of user belief in forming robust behavioral outcomes.

The second path featured perceived usefulness and flow experience as core conditions, with attitude and confirmation as supportive elements. This suggests that when AIGC is perceived as both effective and enjoyable, sustained use can occur even without high satisfaction. This configuration reflects the importance of simultaneous rational and emotional engagement, expanding prior work on user immersion and sustained behavior in digital settings (Salloum et al., 2023; Wu et al., 2022).

The third configuration showed that even when PEOU and flow experience are peripheral, the combination of confirmation, satisfaction, and attitude remains sufficient to predict continued use. This indicates that while emotional and usability-related factors may play supporting roles, cognitive evaluations and affective trust are central drivers. Such findings are consistent with prior fsQCA studies (Song et al., 2024; Tyagi & Krishankumar, 2024) and affirm that there is no single route to technology adoption—different teachers may reach the same outcome through different motivational structures.

In summary, these three fsQCA configurations combine different core and peripheral conditions, supporting the general trend found in PLS-SEM analysis and further demonstrating diverse paths to achieving high continuous intention to use (CITU) in education. These new findings suggest that fostering teachers' continued use of AIGC technology does not only rely on a single factor with the greatest impact. Rather, multiple effective combinations can achieve the goal. Finally, the importance and influence of each characteristic vary in different configurations, suggesting that a mix-and-match strategy should be adopted in different environments to achieve optimal outcomes.

6. Implications

6.1 Theoretical Implications

This study provides several theoretical contributions. First, this study introduces a hybrid model that integrates the Technology Acceptance Model (TAM), Expectation Confirmation Model (ECM), and Flow Theory to predict preschool teachers' continuous intention to use AIGC technologies. While prior research on AIGC has primarily focused on higher education, its application in early childhood education has been largely overlooked. This integrated framework captures both cognitive and emotional dimensions of technology adoption, thereby offering a more comprehensive explanation of behavioral intention in the preschool context.

Second, the findings highlight that flow experience and satisfaction exert stronger effects on continuance intention than perceived usefulness. Specifically, the path coefficients for flow experience and satisfaction exceed that of perceived usefulness by 0.08 and 0.14, respectively. The f^2 effect sizes further reinforce this pattern. Additionally, in the fsQCA configurations, perceived usefulness needs to be matched with flow experience to serve as the core condition. These results underscore the critical role of affective engagement in driving sustained use, suggesting that emotional factors may outweigh purely functional evaluations in shaping long-term adoption. The study also identifies confirmation, satisfaction, and flow experience as key factors that enhance teachers' perceived usefulness and continuous intention to use. Among them, confirmation emerged as the strongest predictor of perceived usefulness, while flow experience significantly shaped positive attitudes, enriching the theoretical understanding of motivational mechanisms behind AIGC use.

Methodologically, the combined application of PLS-SEM and fsQCA enhances the analytical depth by addressing both symmetric and asymmetric relationships. PLS-SEM clarifies the net effects and directional strengths between variables, while fsQCA identifies multiple sufficient configurations leading to high continuance intention. This dual approach reveals that different combinations of cognitive, emotional, and experiential factors can yield similar behavioral outcomes. The study thus demonstrates the value of integrating variance-based and set-theoretic methods to better capture the multifaceted nature of technology adoption in education.

6.2 Practical Implications

The results also provide actionable recommendations for stakeholders aiming to foster the sustainable use of AIGC in preschool education. First, confirmation is pivotal for enhancing perceived usefulness. Educational technology providers should prioritize mechanisms that support expectation alignments, such as offering real-time feedback, usage analytics, and teacher training resources. These can help educators experience early success with AIGC, thereby reinforcing its perceived instructional value.

Second, satisfaction significantly drives continuance intention. To enhance satisfaction, AIGC systems should offer reliable performance and intuitive interfaces that align with the pedagogical routines of preschool teachers. Simple, stable, and enjoyable platforms can promote positive user experiences and long-term commitment.

Third, flow experience plays a key role in shaping both attitude and intention. Developers are encouraged to design interactive features that foster immersion—such as gamified elements, adaptive content creation, or dynamic visualizations. These elements can enhance user engagement and emotional involvement, which are particularly important in the affect-rich context of early childhood education.

ISSN: 0034-8082

Finally, the fsQCA findings suggest that different teachers may reach sustained adoption through different pathways. Thus, education administrators and platform designers should adopt differentiated support strategies tailored to varying combinations of user needs and experiences (e.g., satisfaction, confirmation, or flow engagement). By drawing on both PLS-SEM and fsQCA insights, decision-makers can develop flexible, evidence-based interventions that accommodate diverse motivational profiles and teaching environments, ultimately enhancing the effective integration of AIGC in early learning contexts.

7. Limitations and Future Research

Despite offering meaningful insights, this study has several limitations that should be addressed in future research. First, the data were collected at a single point in time, which limits the ability to capture temporal changes in teachers' perceptions and behaviors. As teachers accumulate experience with AIGC tools, their attitudes and usage intentions may evolve. Future studies could adopt longitudinal designs to explore how these variables shift over time, thereby providing a more dynamic understanding of adoption behavior.

Second, the sample was limited to preschool teachers in China, which may constrain the generalizability of the findings. Cultural, institutional, and infrastructural differences across regions may influence technology acceptance. Future research should include more diverse populations across geographic regions and educational settings to validate the model in broader contexts and test for cross-cultural applicability.

Third, while the current model integrates TAM, ECM, and Flow Theory, it does not account for other influential variables such as social influence, facilitating conditions, or performance expectancy. Future studies could extend the model by incorporating additional theoretical frameworks—such as the Unified Theory of Acceptance and Use of Technology (UTAUT)—to capture a more comprehensive range of determinants influencing AIGC adoption.

Lastly, the exclusive use of quantitative methods may limit the depth of contextual insights. Incorporating qualitative approaches such as interviews, focus groups, or classroom observations could help uncover nuanced barriers and facilitators in teachers' real-world experiences with AIGC technologies. This mixed-methods approach would enhance both the interpretive richness and practical relevance of future investigations.

8. Conclusion

This study developed and tested an integrated model combining the Technology Acceptance Model (TAM), Expectation Confirmation Model (ECM), and Flow Theory to investigate the cognitive, emotional, and behavioral determinants of preschool teachers' continuous intention to use Artificial Intelligence Generated Content (AIGC) technologies. Based on survey data from 433 teachers and dual-method analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Fuzzy Set Qualitative Comparative Analysis (fsQCA), the findings reveal several key insights.

PLS-SEM results demonstrate that confirmation and perceived usefulness are the strongest cognitive drivers, with confirmation exerting a large effect on perceived usefulness ($\beta = 0.505$, $f^2 = 0.343$) and satisfaction ($\beta = 0.349$), while perceived usefulness directly influences attitude ($\beta = 0.530$, $f^2 = 0.442$) and indirectly shapes continued use intention. Satisfaction, which is jointly shaped by both confirmation and usefulness, shows a significant direct effect on continuance intention (β = 0.280). In contrast, perceived ease of use has a relatively minor role, operating mainly through indirect pathways. Flow experience, representing emotional immersion, is found to significantly influence both attitude and continuance intention, highlighting the importance of affective engagement in preschool contexts. Altogether, these results validate the theoretical model, supporting all eleven proposed hypotheses and explaining 51.8% of the variance in continuance intention.

Complementing these findings, the fsQCA results identify three distinct sufficient configurations that lead to high continuance intention. These include combinations centered on (1) attitude, satisfaction, and confirmation, (2) perceived usefulness and flow experience, and (3) confirmation, satisfaction, and attitude—even when flow and ease of use are peripheral. These asymmetrical insights emphasize that no single factor dominates across all users; instead, different combinations of cognitive trust, emotional engagement, and experiential alignment jointly shape sustained technology use.

Together, these findings offer a comprehensive understanding of how preschool teachers develop sustained behavioral intention toward AIGC, grounded in both rational assessment and emotional resonance. This contributes to both theoretical advancement and practical guidance for AIGC adoption in early childhood education.

REFERENCES

Al-Nuaimi, M. N., & Al-Emran, M. (2021). Learning management systems and technology acceptance models: A systematic review. *Education and Information Technologies*, *26*(5), 5499–5533.

Al-Rahmi, A. M., Al-Rahmi, W. M., Alturki, U., Aldraiweesh, A., Almutairy, S., & Al-Adwan, A. S. (2022). Acceptance of mobile technologies and M-learning by university students: An empirical investigation in higher education. *Education and Information Technologies*, *27*(6), 7805–7826.

Alshammari, S. H., & Babu, E. (2025). The mediating role of satisfaction in the relationship between perceived usefulness, perceived ease of use and students' behavioural intention to use ChatGPT. *Scientific Reports*, *15*(1), 7169.

Amyatun, R. L., & Kholis, A. (2023). Can Artificial Intelligence (AI) like QuillBot AI assist students' writing skills? Assisting learning to write texts using AI. *ELE Reviews: English Language Education Reviews*, *3*(2), 135–154.

Antonietti, C., Cattaneo, A., & Amenduni, F. (2022). Can teachers' digital competence influence technology acceptance in vocational education? *Computers in Human Behavior*, *132*, 107266.

Barbuto, L. M., Swaminathan, S., Trawick-Smith, J., & Wright, J. L. (2003). The role of the teacher in scaffolding children's interactions in a technological environment: How a technology project is transforming preschool teacher practices in urban schools. *Proceedings of the International Federation for Information Processing Working Group 3.5 Open Conference on Young Children and Learning Technologies-Volume 34*, 13–20.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 351–370.

Brito, R., & Dias, P. (2017). Digital technologies, learning and school: Practices and perceptions of young children (under 8) and their parents. *The Online Journal of New Horizons in Education*, *7*(1), 64–76.

Burrough, P. A. (1989). Fuzzy mathematical methods for soil survey and land evaluation. *Journal of Soil Science*, *40*(3), 477–492.

Cheah, J.-H., Memon, M. A., Chuah, F., Ting, H., & Ramayah, T. (2018). Assessing reflective models in marketing research: A comparison between pls and plsc estimates. *International Journal of Business & Society*, *19*(1).

Chen, J.-L. (2011). The effects of education compatibility and technological expectancy on e-learning acceptance. *Computers & Education*, *57*(2), 1501–1511.

Chiu, Y.-P., & Chen, C.-C. (2023). Learning Flow and Continuous Intention toward Online Remote Learning: An Integrated Framework. *International Journal of Research in Education and Science*, *9*(2), 351–364.

Chuah, S. H.-W., Aw, E. C.-X., & Yee, D. (2021). Unveiling the complexity of consumers' intention to use service robots: An fsQCA approach. *Computers in Human Behavior*, *123*, 106870.

Cullen, T. A., & Greene, B. A. (2011). Preservice teachers' beliefs, attitudes, and motivation about technology integration. *Journal of Educational Computing Research*, *45*(1), 29–47.

Dai, Y., Huang, Y., Zhang, Y., & Xu, X. (2023). Why technology-supported classrooms: An analysis of classroom behavior data from AIGC. *2023 International Conference on Intelligent Education and Intelligent Research (IEIR)*, 1–17.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340.

ISSN: 0034-8082

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003.

Deng, L., Turner, D. E., Gehling, R., & Prince, B. (2010). User experience, satisfaction, and continual usage intention of IT. *European Journal of Information Systems*, *19*(1), 60–75.

DiCerbo, K. (2021). Why Not Go All-In with Artificial Intelligence? *International Conference on Human-Computer Interaction*, 361–369.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J. R. G., Gruber, B., Lafourcade, B., Leitão, P. J., & others. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, *36*(1), 27–46.

Dul, J. (2016). Identifying single necessary conditions with NCA and fsQCA. *Journal of Business Research*, *69*(4), 1516–1523.

Eraslan Yalcin, M., & Kutlu, B. (2019). Examination of students' acceptance of and intention to use learning management systems using extended TAM. *British Journal of Educational Technology*, *50*(5), 2414–2432.

Guo, J., Ma, Y., Li, T., Noetel, M., Liao, K., & Greiff, S. (2024). Harnessing Artificial Intelligence in Generative Content for enhancing motivation in learning. In *Learning and Individual Differences* (p. 102547). Elsevier.

Guo, Z., Xiao, L., Seo, C., & Lai, Y. (2012). Flow Experience and Continuance Intention Toward Online Learning: An Integrated Framework. *ICIS 2012 Proceedings*, *6*. https://aisel.aisnet.org/icis2012/proceedings/ISCurriculum/6

Hamid, A. A., Razak, F. Z. A., Bakar, A. A., & Abdullah, W. S. W. (2016). The effects of perceived usefulness and perceived ease of use on continuance intention to use e-government. *Procedia Economics and Finance*, *35*, 644–649.

Hashim, H., Mohamad, S. A., Hamzah, H. C., Halid, R. A., & Azer, I. (2023). The Role of Perceived Usefulness and Confirmation in Influencing Student's Satisfaction on Online Distance Learning. *Asian Journal of University Education*, *19*(2), 294–306.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*, 115–135.

Ho, J., Plewa, C., & Lu, V. N. (2016). Examining strategic orientation complementarity using multiple regression analysis and fuzzy set QCA. *Journal of Business Research*, *69*(6), 2199–2205.

Hoffman, D. L., & Novak, T. P. (2009). Flow online: Lessons learned and future prospects. *Journal of Interactive Marketing*, *23*(1), 23–34.

Huang, W., Wang, T., & Tong, Y. (2024). The effect of gamified project-based learning with AIGC in information literacy education. *Innovations in Education and Teaching International*, 1–15.

Jackson, S. A., & Marsh, H. W. (1996). Development and validation of a scale to measure optimal experience: The Flow State Scale. *Journal of Sport and Exercise Psychology*, *18*(1), 17–35.

Jin, J., Yang, M., Hu, H., Guo, X., Luo, J., & Liu, Y. (2024). Empowering design innovation using AI-generated content. In *Journal of Engineering Design* (pp. 1–18). Taylor & Francis.

Kaya, B., Abubakar, A. M., Behravesh, E., Yildiz, H., & Mert, I. S. (2020). Antecedents of innovative performance: Findings from PLS-SEM and fuzzy sets (fsQCA). *Journal of Business Research*, *114*, 278–289.

Khan, M. I., & Saleh, M. A. (2023). Facebook users' satisfaction and intention to continue using it: Applying the expectation confirmation model. *Social Science Computer Review*, *41*(3), 983–1000.

Kim, Y. J., Chun, J. U., & Song, J. (2009). Investigating the role of attitude in technology acceptance from an attitude strength perspective. *International Journal of Information Management*, *29*(1), 67–77.

Kline, R. B. (2012). Assumptions in structural equation modeling. *Handbook of Structural Equation Modeling*, *111*, 125.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration (Ijec)*, *11*(4), 1–10.

Li, X., Zhang, J., & Yang, J. (2024). The effect of computer self-efficacy on the behavioral intention to use translation technologies among college students: Mediating role of learning motivation and cognitive engagement. *Acta Psychologica*, *246*, 104259.

Liang, C., Du, H., Sun, Y., Niyato, D., Kang, J., Zhao, D., & Imran, M. A. (2024). Generative AI-driven semantic communication networks: Architecture, technologies and applications. *IEEE Transactions on Cognitive Communications and Networking*.

López-Bonilla, L. M., & López-Bonilla, J. M. (2017). Explaining the discrepancy in the mediating role of attitude in the TAM. *British Journal of Educational Technology*, *48*(4), 940–949.

Lorah, J. (2018). Effect size measures for multilevel models: Definition, interpretation, and TIMSS example. *Large-Scale Assessments in Education*, *6*(1), 1–11.

Lu, G., Hussin, N. B., & Sarkar, A. (2024). Navigating the future: Harnessing artificial intelligence generated content (AIGC) for enhanced learning experiences in higher education. *2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE)*, 1–12.

Ma, X., Ding, X., Tang, X., Zhang, S., & Diao, J. (2024). Risks, Strategies, and Prospects of Generative Artificial Intelligence in Digital Education: A Policy Content Analysis Perspective. *Proceedings of the 3rd International Conference on Educational Innovation and Multimedia Technology, EIMT 2024, March 29–31, 2024, Wuhan, China*.

Michailidis, L., Balaguer-Ballester, E., & He, X. (2018). Flow and immersion in video games: The aftermath of a conceptual challenge. *Frontiers in Psychology*, *9*, 1682.

Molwus, J. J., Erdogan, B., & Ogunlana, S. O. (2013). Sample size and model fit indices for structural equation modelling (SEM): The case of construction management research. In *ICCREM 2013: Construction and Operation in the Context of Sustainability* (pp. 338–347).

Pappas, I. O., Papavlasopoulou, S., Mikalef, P., & Giannakos, M. N. (2020). Identifying the combinations of motivations and emotions for creating satisfied users in SNSs: An fsQCA approach. *International Journal of Information Management*, *53*, 102128.

Philip, G. C., & Soo-Young, M. (2013). An investigation of student expectation, perceived performance and satisfaction of e-textbooks. *Journal of Information Technology Education. Innovations in Practice*, *12*, 287.

Purwanto, A., & Sudargini, Y. (2021). Partial least squares structural squation modeling (PLS-SEM) analysis for social and management research: A literature review. *Journal of Industrial Engineering & Management Research*, *2*(4), 114–123.

Ragin, C. C., & Fiss, P. C. (2008). Net effects analysis versus configurational analysis: An empirical demonstration. *Redesigning Social Inquiry: Fuzzy Sets and Beyond*, *240*, 190–212.

Rahi, S., Alghizzawi, M., & Ngah, A. H. (2023). Factors influence user's intention to continue use of e-banking during COVID-19 pandemic: The nexus between self-determination and expectation confirmation model. *EuroMed Journal of Business*, *18*(3), 380–396.

Ramlall, I. (2016). Model fit evaluation. In *Applied Structural Equation Modelling for Researchers and Practitioners* (pp. 61–74). Emerald Group Publishing Limited.

Rasoolimanesh, S. M., Ringle, C. M., Sarstedt, M., & Olya, H. (2021). The combined use of symmetric and asymmetric approaches: Partial least squares-structural equation modeling and fuzzy-set qualitative comparative analysis. *International Journal of Contemporary Hospitality Management*, *33*(5), 1571–1592.

Runhaar, P. (2017). How can schools and teachers benefit from human resources management? Conceptualising HRM from content and process perspectives. *Educational Management Administration & Leadership*, *45*(4), 639–656.

Salloum, S., Al Marzouqi, A., Alderbashi, K. Y., Shwedeh, F., Aburayya, A., Al Saidat, M. R., & Al-Maroof, R. S. (2023). Sustainability model for the continuous intention to use metaverse technology in higher education: A case study from Oman. *Sustainability*, *15*(6), 5257.

Salonen, A., Zimmer, M., & Keränen, J. (2021). Theory development in servitization through the application of fsQCA and experiments. *International Journal of Operations & Production Management*, *41*(5), 746–769.

Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair Jr, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy*, *5*(1), 105–115.

Sharma, L., & Srivastava, M. (2020). Teachers' motivation to adopt technology in higher education. *Journal of Applied Research in Higher Education*, *12*(4), 673–692.

Shi, D., & Maydeu-Olivares, A. (2020). The effect of estimation methods on SEM fit indices. *Educational and Psychological Measurement*, *80*(3), 421–445.

Shiau, W.-L., & Chau, P. Y. (2016). Understanding behavioral intention to use a cloud computing classroom: A multiple model comparison approach. *Information & Management*, *53*(3), 355–365.

Song, Q., Zhang, J., Wang, H., Zhang, Z., & Zhou, Q. (2024). Configuring Factors Influencing Science Teachers' Intention to Use Virtual Experiments in China: An fsQCA-Based Study. *Journal of Science Education and Technology*, *33*(3), 300–315.

Spreng, R. A., & Olshavsky, R. W. (1993). A desires congruency model of consumer satisfaction. *Journal of the Academy of Marketing Science*, *21*, 169–177.

Streukens, S., & Leroi-Werelds, S. (2016). Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results. *European Management Journal*, *34*(6), 618–632.

Svetsky, S., & Moravcik, O. (2019). Some barriers regarding the sustainability of digital technology for long-term teaching. *Proceedings of the Future Technologies Conference (FTC) 2018: Volume 1*, 950–961.

Teo, T., Lee, C. B., Chai, C. S., & Wong, S. L. (2009). Assessing the intention to use technology among pre-service teachers in Singapore and Malaysia: A multigroup invariance analysis of the Technology Acceptance Model (TAM). *Computers & Education*, *53*(3), 1000–1009.

Thong, J. Y., Hong, S.-J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human-Computer Studies*, *64*(9), 799–810.

Tseng, H., Yi, X., & Cunningham, B. (2022). Learning technology acceptance and continuance intention among business students: The mediating effects of confirmation, flow, and engagement. *Australasian Journal of Educational Technology*, *38*(3), 70–86.

Tyagi, S. K., & Krishankumar, R. (2024). Examining interactions of factors affecting e-learning adoption in higher education: Insights from a fuzzy set qualitative and comparative analysis. *Journal of Science and Technology Policy Management*, *15*(6), 1387–1407.

Vafaei-Zadeh, A., Nikbin, D., Loo, J., & Hanifah, H. (2024). Unlocking Generation Y's continuance intentions in personal cloud storage services: An extended expectation confirmation model analysis. *The Electronic Library*, *42*(5), 827–847.

Vega, J., Rodriguez, M., Check, E., Moran, H., & Loo, L. (2024). Duolingo evolution: From automation to Artificial Intelligence. *2024 IEEE Colombian Conference on Applications of Computational Intelligence (ColCACI)*, 1–6.

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, *67*, 221–232.

Wu, C.-H., Liu, C.-H., & Huang, Y.-M. (2022). The exploration of continuous learning intention in STEAM education through attitude, motivation, and cognitive load. *International Journal of STEM Education*, *9*(1), 35.

Wu, J.-H., Tennyson, R. D., & Hsia, T.-L. (2010). A study of student satisfaction in a blended e-learning system environment. *Computers & Education*, *55*(1), 155–164.

Xia, Y. X., & Chae, S. W. (2021). Sustainable development of online group-buying websites: An integrated perspective of ECM and relationship marketing. *Sustainability*, *13*(4), 2366.

Xiong, Y., Shi, Y., Pu, Q., & Liu, N. (2024). More trust or more risk? User acceptance of artificial intelligence virtual assistant. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *34*(3), 190–205.

Yang, X. (2024). Mobile learning application characteristics and learners' continuance intentions: The role of flow experience. *Education and Information Technologies*, *29*(2), 2259–2275.

Zhang, Y., Lu, X., Zhang, M., Ren, B., Zou, Y., & Lv, T. (2022). Understanding farmers' willingness in arable land protection cooperation by using fsQCA: Roles of perceived benefits and policy incentives. *Journal for Nature Conservation*, *68*, 126234.

Zheng, H., Qian, Y., Wang, Z., & Wu, Y. (2023). Research on the Influence of E-Learning Quality on the Intention to Continue E-Learning: Evidence from SEM and fsQCA. *Sustainability*, *15*(6), 5557.