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Understanding AI ethics in education with a LLM-based chatbot: Evidence from PLS-SEM and fsQCA analyses

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Article

Keywords: AI ethics, PLS-SEM, fsQCA, Technology acceptance model

Posted Date: March 30th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8618094/v1

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Additional Declarations: No competing interests reported.

Abstract

As Artificial Intelligence (AI) becomes increasingly and widely integrated in education, fostering teachers' understanding of AI ethics has become critical. This study investigates the acceptance of a chatbot based on a Large Language Model (LLM), designed to enhance teachers' understanding of AI ethics in education. A mixed-methods approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA) was applied in the current study with 142 participants. Findings show that the content accuracy, system functionality and stability significantly influence perceived ease of use and perceived usefulness. FsQCA further revealed five sufficient configurations associated with high continuance intention. These findings provide practical guidance for designing AI-supported learning environments and offer directions for future research.

Introduction

With the continuous innovation of technology, Generative Artificial Intelligence (GenAI) is becoming increasingly and widely used in the field of education, and its rapid integration in educational environments is profoundly changing the way of teaching and learning. While GenAI offers significant opportunities for enhancing teaching efficiency and personalized instruction (Bozkurt, 2023; Wang et al., 2023), it also raises a range of key ethical questions about transparency, fairness, accountability, and changing roles of educators (Jobin et al., 2019; Kazim & Koshiyama, 2021; Nguyen et al., 2023). Research suggests that over-reliance on AI can impair the ability of teachers and students to think independently and creativity, leading to academic misconduct such as cheating, plagiarism, or using AI to complete assignments and write essays (Bakar-Corez & Kocaman-Karoglu, 2024; Kasneci et al., 2023). Additionally, AI-generated answers and content can hinder critical thinking for teachers and students, bypassing traditional learning processes, thereby damaging their academic development and the credibility of the education system (Ipek et al., 2023). Additionally, the information generated by GenAI tools may be inaccurate or biased, further increasing the risk of academic dishonesty and copyright infringement (Baek & Kim, 2023; Eke, 2023). In response to the growing ethical issue of AI, studies have pointed out that a complete rejection of AI is not a viable solution (Lim et al., 2023). Many scholars and educational institutions advocate for an open and cautious approach, emphasizing the development of clear frameworks and clear guiding principles to harness the full potential of AI while effectively mitigating its potential risks (Uddin, 2024).

While numerous ethical guidelines and policies for AI have emerged in recent years, these norms often remain abstract and lack concrete implementation guidance. Thus, teachers struggle to clearly identify and respond to the ethical risks and responsibilities of using AI in educational contexts (Nikolopoulou, 2021). At the same time, teachers play a vital role in guiding students to use AI responsibly and consciously, their ethical awareness and literacy are essential for the sustainable integration of AI in education (Ayanwale et al., 2024). However, the opportunities for teachers to participate in AI ethics learning are still limited and somehow ineffective. The lack of structured professional development pathways limits educators' ability to meaningfully engage in and contribute to discussions and practices

related to AI ethics (Lim et al., 2023). This suggests that existing policies and guidelines alone are insufficient to address current challenges, highlighting the need for targeted training mechanisms to systematically enhance teachers' cognition, understanding, and practical competence in AI ethics (Mouta et al., 2025). Conventional training approaches frequently prove inadequate in addressing the specific demands of this domain. On the one hand, conventional training is frequently detached from practical teaching contexts and lacks situational relevance. On the other hand, its content often lacks flexibility and continuity, limiting its effectiveness in keeping pace with fast-evolving technological developments.(Hagendorff, 2020; Wiese et al., 2025). Accordingly, it is imperative to design innovative and scalable training models that facilitate teachers' continuous professional development and promote deep, context-aware ethical reflection. To address this need, this study introduces chatbot, a large language model-based chatbot developed via the LangChain framework, designed to support teachers in enhancing their ethical literacy in the context of artificial intelligence.

To understand teachers' intention to use the chatbot and the factors influencing it, this study adopts the Technology Acceptance Model (TAM) to examine how key variables—such as perceived usefulness and perceived ease of use—affect their usage intentions. TAM has been widely substantiated in many fields to effectively explain user behavior in adopting information systems, particularly focusing on perceived usefulness and perceived ease of use as key determinants factors affecting user intention and actual usage behavior (Barrett et al., 2021; Davis, 1989; Wang et al., 2021). But as research advances further, more and more scholars have begun to pay attention to other potential influencing factors other than the TAM model (Barrett et al., 2021; Kim & Lee, 2014). Studies have shown that system quality is also an important factor affecting user adoption behavioral intention to adopt technology (Shen & Liu, 2022; Xu et al., 2013; Zheng et al., 2013), high-quality systems often enhance user trust, satisfaction, and overall user experience, thereby increasing their willingness to adopt and continue using them (Almaiah & Mulhem, 2019; Al-Adwan et al., 2022). This study introduces a specific dimension of AI ethics education based on TAM, focusing on three key factors affecting the system quality of the chatbot: content accuracy, system functionality and stability, and technical support. These factors are hypothesized to affect users' perceptions of usefulness and ease of use, further affecting their behavioral intentions to continue using the chatbot. By integrating PLS-SEM and fsQCA, this study comprehensively reveals the causal relationships and multiple configuration paths that affect teachers' willingness to use AI ethics learning tools, providing a new theoretical perspective for understanding their motivations.

Literature review

Technology acceptance model

The Technology Acceptance Model (TAM) was first introduced by Davis (1989) to explore the degree of user acceptance of emerging technologies. As a maturing theoretical model, TAM has been widely used to understand the key factors influencing user adoption and sustained use of technological innovations (Al-Emran et al., 2018; Teo, 2010). Over the past decades, it has been successfully applied in various fields, including mobile learning (Almaiah et al., 2016; Gómez-Ramirez et al., 2019), smart learning

environments (Hu, 2022), virtual learning platforms (Al-Adwan et al., 2023), and online education systems (Han & Sa, 2022; Waheed & Jam, 2010). With the expansion of its application contexts, an increasing number of studies have explored the applicability of the TAM model in the context of diversification, and proposed extensions to its original structure. The model emphasizes two key constructs: Perceived usefulness (PU) and perceived ease of use (PEU), which are considered crucial in determining users' attitudes and behavioral intentions toward a particular technology. Perceived usefulness refers to the degree to which users believe that a technology can improve their performance, while perceived ease of use refers to the degree to which users find the technology free from effort (Davis, 1989; Liu et al., 2010). These perceptions directly influence users' intention to use the technology, which serves as the primary outcome variable in TAM. It is widely regarded as a strong predictor of actual usage behavior and is critical in assessing the effectiveness of educational technology adoption (Barrett et al., 2021; Scherer et al., 2019; Zhang et al., 2023).

Numerous studies have consistently shown that among the key constructs of the TAM, PU is typically a strong predictor of teachers' intentions to adopt new technologies. Meta-analyses by Ma and Liu (2004) and King and He (2006) show that PU has a wide range of coefficient values, indicating its strong impact on users' intentions to use various technological tools. This effect is particularly evident in the educational context, where PU serves as a crucial determinant of teachers' intentions to adopt new technologies. When teachers perceive that a technology can enhance instructional effectiveness, streamline teaching processes, or facilitate student learning, they are more likely to adopt it in their teaching practices (Bai et al., 2021; Scherer et al., 2015). Similarly, complementing the role of PU, PEU is likewise supported by educational technology research as a key predictor of teachers' ITU. For instance, Teo (2010) found that PEU had a significant positive influence on pre-service teachers' intention to use educational software, indicating that ease of system interaction is an important motivational factor. Weng et al. (2018) also confirmed in their TAM-based study on elementary school teachers' use of multimedia materials that PEU not only has a direct effect on ITU, but also exerts an indirect effect through attitude toward use. These findings provide the basis for the following two hypotheses of this study

H1. PEU will have a positive and significant effect on teachers' ITU of the chatbot.

H2. PU will have a positive and significant effect on teachers' ITU of the chatbot.

The quality of learning system

The Information System Success Model (IS Success Model), proposed by DeLone and McLean (1992), is one of the most widely adopted frameworks for evaluating the effectiveness of information systems. This model conceptualizes system success through three primary dimensions: information quality, system quality, and service quality. Subsequently, Rai et al. (2002) provided empirical validation demonstrating that the three dimensions of the information system success model are key constructs and factors influencing IS usage and performance. This study modifies the original IS success model to align more closely with the educational application scenario of the AI ethics learning tool. Specifically,

information quality is revised as “content accuracy”, referring to the relevance and correctness of the ethical content generated by the chatbot; system quality is reformulated as “system functionality and stability”, capturing the chatbot’s operational reliability and technical performance; and service quality is renamed “technical support”, assessing the quality and responsiveness of assistance provided to users. This study draws on Cheng’s (2012) empirical findings that information quality, system quality, and service quality are the key quality antecedent variables influencing users’ acceptance of e-learning systems. Based on the research conclusions of Cheng (2012), this study defines these three quality dimensions as external antecedents affecting teachers’ PU and PEU. In the proposed research model, these quality dimensions function as external variables that influence teachers’ system perceptions and ultimately shape their intention to adopt the AI-based ethical learning tool.

Content Accuracy

Content accuracy refers to the ability of a system to provide correct, trustworthy, and up-to-date information (DeLone & McLean, 2003; Sassano et al., 2010). As a key component of information quality, content accuracy is fundamental in shaping users’ trust and overall evaluation of a technology system, particularly in knowledge-intensive environments (Nelson et al., 2005). In AI-supported tools, maintaining high content accuracy is particularly important to ensure teaching reliability and professional credibility as content is dynamically generated (Almuhanna, 2024). Seddon (1997) points out that the user’s perception of the usefulness of a system is greatly influenced by the quality of the information it provides. Machdar (2016) further emphasized that when users rely on system-generated content for decision-making, higher information quality makes the system more likely to be perceived as useful and trustworthy. For teachers, the content accuracy of AI-generated tools significantly enhances their confidence in applying these tools to teaching tasks, such as writing assistants or instructional simulations (Aljuaid, 2024; Kim & Kim, 2022). In addition, studies have found that teachers are more inclined to adopt systems that provide accurate and highly relevant resources in AI-based intelligent recommendation systems (Siafis et al., 2024).

Beyond fostering users’ perceived usefulness, content accuracy also facilitates perceived ease of use. When information is accurate and clearly presented, users can more easily understand how to operate the system, thereby enhancing their perception of its ease of use (Almaiah & Al Mulhem, 2019). For example, in digital assessment systems, when teachers receive accurate and well-structured feedback, they are less likely to need additional explanation or manual correction, which reduces disruptions during use and enhances the system’s operability (Patra et al., 2022). Moreover, in language education, teachers generally believe that high content accuracy as a key factor in reducing the need for repeated verification of system outputs. This reduction in operational pressure and technical anxiety further strengthens their perception of system ease of use (Belda-Medina & Calvo-Ferrer, 2022; Hsu, 2016).

Based on these insights, the following hypotheses are proposed:

H3. CA of the chatbot will be a positive and significant predictor of PU.

H4. CA of the chatbot will be a positive and significant predictor of PEU.

System functionality and stability

System functionality and stability refer to the overall technical performance demonstrated by the system during its operation, including operational stability, functional reliability, system response speed, interface usability, and cross-platform compatibility (Almaiah & Alamri, 2018; DeLone & McLean, 2003; Giang & Nga, 2024; Kim & Lee, 2014; Ohliati & Abbas, 2019). This variable examines the system's ability to provide stable, uninterrupted service, ensure smooth access to its functions, and support users in completing tasks efficiently. System functionality and stability are key characteristics of a information system that can significantly influence users' attitudes and behaviors towards its use (Almaiah & Al Mulhem, 2019).

A system with comprehensive features and high stability can provide a more efficient and smoother user experience, fostering users' belief that it can effectively meet their needs and thereby enhancing its perceived usefulness (Kim & Lee, 2014). According to Farhan et al. (2019), system quality dimensions—including reliability, response time, and interface design—have a significant impact on teachers' perceived usefulness of school e-learning systems. When a system is highly functional and stable, teachers are more likely to trust the technology and believe in its potential to improve teaching organization, classroom interaction, and student engagement. As Du et al. (2022) point out, when evaluating the usefulness of virtual reality technology in classroom teaching, teachers pay particular attention to whether the system can maintain continuous and stable operation and whether it can support diverse teaching situations.

System functionality and stability play a critical role in shaping users' PEU. A successful online learning system should be evaluated in terms of user-friendliness and the effectiveness of feedback mechanisms to ensure that learners can operate smoothly and receive timely support (Giang & Nga, 2024; Mahande et al., 2019). For teachers, A reliable and user-friendly system allows them to navigate it easily, build teaching confidence, and minimize frustration (Ghavifekr & Rosdy, 2015; Padayachee, 2017). Building on this, Ke et al. (2012) demonstrated that systems with well-designed interfaces and stable performance can help teachers master and use the technology to teach more efficiently and increase student participation in the classroom.

Based on these insights, the following hypotheses are proposed:

H5. SFS of the chatbot will positively and significantly predict PU.

H6. SFS of the chatbot will positively and significantly predict PEU.

Technical Support

Technical support refers to the level of service provided by the information system to assist users. It includes the timeliness of responses, the effectiveness of problem resolution, the professionalism of

support staff, and the adequacy of user training and guidance (Dwivedi et al., 2011; Grönroos, 1984; Ting et al., 2011). During system usage, users may encounter system errors, difficulties in operating specific functions, or incompatibility due to system updates. Timely intervention by technical support can significantly reduce barriers to use and enhance user trust and satisfaction with the system (Gajic & Boolaky, 2015; Hu et al., 2009; Kalankesh et al., 2020).

Technical support has a positive impact on PU by improving the reliability and operation guarantee of the system and enhancing the use's trust in the actual utility of the system. In educational contexts, teachers are often not technical experts. When faced with unfamiliar teaching tools, timely and professional technical assistance can help them better perceive the system's support for their teaching objectives (Ghavifekr & Rosdy, 2015; Padayachee, 2017). In addition, empirical studies on teachers' use of virtual reality technology in the classroom have shown that technical support has a significant impact on the perceived usefulness of their systems, which in turn further affects teachers' user satisfaction (Du et al., 2022). This further shows that technical support, as a core element of service quality, is a key factor in shaping the perception of teachers' system usefulness.

At the same time, technical support also plays an important role in the user's PEU. Timely and effective assistance can reduce cognitive and technical barriers during operation, allowing teachers to use system functions more smoothly (Arteaga Sánchez et al., 2013; Ibrahim & Shiring, 2022). Empirical research further confirms this view. In a study on the use of WebCT teaching systems by college teachers, Kim and Lee (2014) found that the continuous technical support of the chatbot significantly reduced teachers' uncertainty in the face of technology, thereby improving their overall perception of the ease of use of the system. In addition, Dwivedi et al. (2011) pointed out that technical support improves system usability by providing assistance in key usage links, thereby enhancing the user's perception of system learnability and intuitiveness.

Based on these insights, the following hypotheses are proposed:

H7.TS of the chatbot will be a positive and significant predictor of PU.

H8.TS of the chatbot will be a positive and significant predictor of PEU.

Theoretical confirmatory model

Based on the synthesis of prior studies outlined in Subsections 2.1 and 2.2, this study formulates a confirmatory theoretical framework (see Figure 1) to empirically explore teachers' acceptance of the chatbot. In the proposed model, content accuracy, system functionality and stability, and technical support are included as external variables that influence teachers' perceived ease of use and perceived usefulness, which in turn affect their intention to use the chatbot. This model provides a structured framework for understanding key factors that drive technology adoption.

Research methods

Sample and data collection

The research employed a stratified random sampling method, selecting, teachers from a public university located in southeastern China as the research subjects. A questionnaire was formulated after referring to previous studies and consulting with experts to ensure the validity of the questionnaire. As depicted in Fig. 1, the three structures are named “Content accuracy,” “System function and stability”, and “Technical support.” All items were evaluated using a five-point Likert scale, with a score range from 1 (strongly disagree) to 5 (strongly agree).

To ensure the reliability and validity of the collected data, the research team set a critical criterion: all teachers who participated in the survey must have had at least one month of experience using the chatbot. Figure 2 shows a participant interacting with the chatbot. This criterion not only helps in obtaining feedback based on actual usage experiences but also reduces cognitive biases due to short usage times, ensuring that the research results accurately reflect teachers’ technical acceptance and usage intentions of the chatbot. Under the strict adherence to the above sampling principles and standards, a total of 168 questionnaires were initially collected in this study. After a meticulous screening process, including the elimination of questionnaires with blank filling, missing key information, and arbitrary filling, 142 valid questionnaires were finally retained for further analysis.

Chatbot

This study presents the design of an AI-assisted chatbot for ethical learning and reflection, which integrates a large language model (LLM) through API access. The chatbot leverages the LLM’s natural language processing capabilities to facilitate structured dialogue and critical engagement with ethical issues in educational contexts, aiming to support the development of teachers’ ethical awareness and reasoning.

The chatbot is designed around three main functions: knowledge expansion, case study, and post-learning evaluation to support the acquisition, application, and evaluation of ethical knowledge. Through the knowledge expansion module, teachers can access standardized explanations of fundamental concepts, principles, and common issues related to AI ethics by interacting with a large language model, thereby enhancing their theoretical understanding. The case-based learning module offers a rich repository of educational ethics cases, enabling teachers to engage with concrete scenarios, analyze ethical dilemmas, and internalize ethical knowledge by applying theory to practice. The post-learning assessment module dynamically generates evaluation items to assess teachers’ mastery of ethical knowledge, providing personalized feedback that fosters ongoing reflection and professional growth. Below is a detailed explanation of the functions of each module (see Fig. 3).

Data analysis

This study employed SmartPLS 4.0 for Partial Least Squares Structural Equation Modeling (PLS-SEM), complemented by fuzzy-set Qualitative Comparative Analysis (fsQCA), to comprehensively analyze the factors influencing teachers' intention to continue using the chatbot.

PLS-SEM was selected for its robust handling of small sample sizes (n = 142) and its ability to estimate complex structural models with multiple latent constructs, such as content accuracy, system functionality and stability, technical support, perceived usefulness, perceived ease of use, and intention to use. This method is suitable for exploratory research and theoretical development with low distribution assumptions (Hair et al., 2021).

To enrich the findings and address the complexity of configurations in the user decision-making process, the fsQCA method is also introduced. PLS-SEM is primarily used to test linear net effects between constructs, while fsQCA is able to identify multiple causal paths that lead to the outcome variable—intention to use—through a combination of conditions such as high content accuracy, functional stability, and ease of use. This combined strategy provides both variance-based and set theory-based insights. Data analysis is divided into three steps:

(1) Measurement model assessment, involving the evaluation of indicator loadings, composite reliability, and average variance extracted to ensure the validity and reliability of latent constructs.

(2) Structural model assessment, including estimation of path coefficients and explanatory power (R^2) to test hypothesized relationships among constructs.

(3) FsQCA, which was used to identify sufficient configurations of causal conditions that lead to high continuance intention, thus capturing the multifaceted and equifinal nature of user acceptance in ethical AI learning tools.

Results

Measurement model estimation

The reliability and validity of the latent variables were tested based on previous studies evaluating the measurement model (Hair et al., 2017), as shown in Table 1. All individual projects have a reliability (load) of 0.635 or higher, meeting the criteria for reliability of individual projects (Hajiar, 2018). Internal consistency was assessed using both composite reliability (CR) and Cronbach's alpha. In this study, the Cronbach's alpha ranged from 0.833 to 0.914, exceeding the commonly accepted threshold of 0.7, thereby indicating satisfactory reliability (Onwuegbuzie & Daniel, 2002). Additionally, the CR values for all constructs fell between 0.885 and 0.933, which is well above the minimum recommended level of 0.70 and within the ideal range of 0.70 to 0.90, reflecting strong internal consistency. Convergent validity (CV) was examined through the Average Variance Extracted (AVE). The AVE scores in this study varied between 0.523 and 0.768, all surpassing the benchmark value of 0.50 as proposed by Chin (1998) and

Fornell and Larcker (1981). These results suggest that the measurement model demonstrates adequate convergent validity.

Discriminative validity refers to the ability of a variable to be distinguishable from other variables to some extent. The Fornell-Larcker criterion is a method used to test discriminative validity. According to this criterion, the condition for determining validity is that the square root of the mean variance extraction for each variable should be greater than the correlation coefficient between that variable and any other variable (Fornell & Larcker, 1981). The results in Table 2 show that the square root of the average variance extracted for each variable is greater than its highest correlation coefficient with other variables, thus meeting the requirements for discriminative validity.

In conclusion, this study systematically tests the reliability and validity of the measurement model, and the results show that the factor load of each variable exceeds 0.7, and the internal consistency and aggregate validity meet the standard. This indicates that the measurement model has high reliability and validity, and is suitable for subsequent structural model analysis.

Table 1
CFA results for reliability and validity of measurement items

Construct	Original items	Factor loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Content accuracy	CA1	0.743	0.871	0.907	0.66
	CA2	0.833			
	CA3	0 842			
	CA4	0.781			
	CA5	0.859			
System functionality and stability	SFA1	0.716	0.848	0.885	0.523
	SFA2	0.725			
	SFA3	0.752			
	SFA4	0.751			
	SFA5	0.721			
	SFA6	0.667			
	SFA7	0.727			
Technical support	TS1	0.758	0.833	0.889	0.667
	TS2	0.827			
	TS3	0.852			
	TS4	0.827			
Perceived ease of use	EU1	0 635	0.892	0.916	0.612
	EU2	0.832			
	EU3	0.836			
	EU4	0.829			
	EU5	0.834			
	EU6	0.788			
	EU7	0.697			
Perceived usefulness	U1	0.847	0.914	0.933	0.7
	U2	0.803			
	U3	0.815			

Construct	Original items	Factor loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
	U4	0.878			
	U5	0.789			
	U6	0.885			
Intention to use	WCU1	0.865	0.899	0.93	0.768
	WCU2	0.891			
	WCU3	0.875			
	WCU4	0.875			

Table 2
Discriminant validity results

	Content accuracy	Perceived ease of use	System functionality and stability	Technical support	Perceived usefulness	Intention to use
Content accuracy	0.813					
Perceived ease of use	0.633	0.782				
System functionality and stability	0.644	0.67	0.723			
Technical support	0.404	0.497	0.509	0.817		
Perceived usefulness	0.606	0.871	0.661	0.457	0.837	
Intention to use	0.653	0.67	0.648	0.397	0.716	0.876

Structural model estimation

PLS-SEM analyzes a structural model by the indicators of: (1)R^2 (R-squared/coefficient of determination); (2) Q^2 (The predictive relevance); (3)path coefficient effect size; (4) SRMR (Standardized Mean Root Square Residual); (5) VIF(Variance Inflation Factor); (6) BIC (Bayesian Information Criterion). First, potential multicollinearity in the structural model was examined by calculating the Variance inflation factor (VIF) values, and it was found that all values were below 3.30 (Table 3), well below the recommended threshold of < 5 (Hair et al., 2017). These results confirm that multicollinearity has not

reached a critical level among the predictor constructs in the model. Furthermore, the cross-validated redundancy (Q^2) is greater than zero, indicating that the model has predictive relevance.

The direct path coefficients of the structural model were analyzed to examine the hypothesized relationships between variables. Based on a sample of 142 respondents, the following findings were observed. The analysis of the coefficients in the TAM constructed in Fig. 1 revealed that the path from CA to PEU was small but statistically significant ($\beta = 0.321$, $p < 0.01$), supporting H3. The path from SFS to PEU was also significant ($\beta = 0.374$, $p < 0.01$), supporting H5. In addition, the path from TS to PEU was significant as well ($\beta = 0.176$, $p < 0.05$), providing support for H7. Regarding PU, the path from CA to PU was significant ($\beta = 0.291$, $p < 0.01$), supporting H4, and the path from SFS to PU was also significant ($\beta = 0.406$, $p < 0.01$), supporting H6. However, the path from TS to PU was not statistically significant ($\beta = 0.133$, $p > 0.05$), leading to the rejection of H8. As for ITU, the path from PEU to ITU showed a small positive effect but was not significant ($\beta = 0.191$, $p > 0.05$), so H1 is not supported. In contrast, the path from PU to ITU showed a strong and statistically significant positive effect ($\beta = 0.550$, $p < 0.001$), thus H2 is supported. For a complete representation of the loadings, see Fig. 4 and Table 4.

Table 3
Saturated model results

	R^2	Adj.R^2	Q^2	RMSE	MAE	SRMR	VIF	BIC	Chi-square
PEU	0.541	0.531	0.488	0.731	0.52	0.071	< 3.30	-91.845	1066.211
PU	0.506	0.495	0.439	0.772	0.536			-81.213	
ITU	0.522	0.515	0.441	0.762	0.599			-90.826	

Table 4
Path coefficients and hypothesis testing

Hypothesis	Relationships	Mean	Standard deviation	t-statistics	p-value	Results
H1	PEU -> ITU	0.189	0.137	1.382	0.167	Unsupported
H2	PU -> ITU	0.552	0.132	4.185	0.000	Supported
H3	CA ->PEU	0.318	0.114	2.977	0.003	Supported
H4	CA -> PU	0.296	0.117	2.722	0.007	Supported
H5	SFS -> PEU	0.382	0.132	2.772	0.006	Supported
H6	SFS -> PU	0.404	0.141	2.707	0.007	Supported
H7	TS -> PEU	0.178	0.077	2.225	0.026	Supported
H8	TS -> PU	0.133	0.072	1.815	0.07	Unsupported

Qualitative Comparative Analysis of Fuzzy Sets (fsQCA)

Selection and calibration of variables

Based on the literature and empirical research findings, CA, SFS, TS, PEU, and PU are selected as condition variables, while ITU serves as the outcome variable. Following the approach of Rihoux and Ragin (2009), the 95th percentile, 50th percentile, and 5th percentile of the data are set as calibration anchors, representing full membership, the crossover point, and full non-membership, respectively. The calibration process is carried out using fsQCA 4.1 software.

Necessity analysis of conditions

Before conducting the configurational analysis, the necessity of each condition variable (including its negation) is tested to determine whether it constitutes a necessary condition for ITU. This is done through an analysis of the necessity of each individual condition variable for the outcome variable (as shown in the Table 5). The results indicate that the consistency of all condition variables is less than 0.9, meaning that none of them are necessary conditions for a high/low ITU. Therefore, further configurational analysis is required.

Table 5
Details of the necessity analyses

Condition Variables	ITU		~ITU	
	Consistency	Coverage	Consistency	Coverage
CA	0.826	0.831	0.649	0.587
~CA	0.590	0.590	0.814	0.808
SFS	0.878	0.799	0.694	0.568
~SFS	0.525	0.656	0.754	0.847
TS	0.773	0.763	0.653	0.580
~TS	0.574	0.648	0.733	0.744
PEU	0.809	0.844	0.621	0.583
~PEU	0.600	0.638	0.834	0.797
PU	0.858	0.833	0.675	0.589
~PU	0.576	0.663	0.808	0.837

Note: “~”denotes the set relationship of “negation” or “complement”

Sufficiency analysis of condition configurations

Following the approach of Pappas & Woodside (2021) and Leppänen (2023), for medium-sized samples ($50 < N < 150$), the frequency threshold is set at 2, and the raw consistency threshold is set at 0.8. After

constructing the truth table, Standard Analyses are performed. Given the numerous factors influencing teachers' ITU in the research context, and the difficulty in measuring the necessity of each factor, the condition variables are uniformly classified as "Present or Absent". In QCA studies, intermediate solutions, which are reasonable, well-founded, and of moderate complexity, are typically the preferred choice for reporting and interpretation. Therefore, the analysis primarily focuses on the intermediate solution, with simple solutions used as supplementary, ultimately identifying the core and peripheral conditions influencing the outcome variable. Under the Intermediate Solution type, eight configurational paths are identified, but the results are not concise. After adjusting the frequency threshold to 3 and performing Standard Analyses again, five configurational paths are obtained. The reduction in the number of paths decreases redundancy between them, making the analysis clearer. While the Solution Coverage of these five paths slightly decreases (from 0.878 to 0.836), it remains at a high level; however, Solution Consistency improves (from 0.788 to 0.850), surpassing the acceptable minimum threshold of 0.8, indicating that the logic of the paths is more robust. The adjustment of the frequency threshold is thus deemed appropriate. Therefore, the five configurational paths presented in Table 6 can be regarded as the sufficient conditions for influencing teachers' intention to continue using the system in the given research context.

Table 6
Sufficiency Analysis of Condition Configurations

Condition Variables	**ITU**				
	1	**2**	**3**	**4**	**5**
CA	•		×	×	×
SFS	⊙	⊙	⊙	×	×
TS	⊙			×	⊙
PEU		⊙	×	⊙	×
PU		•	×	×	•
Consistency	0.918	0.907	0.860	0.915	0.937
Raw coverage	0.664	0.744	0.398	0.294	0.325
Unique coverage	0.026	0.084	0.023	0.009	0.002
Solution consistency	0.850				
solution coverage	0.836				

Note: "•" denotes peripheral conditions, "×" denotes non−existent conditions (negated conditions), "⊙" denotes core conditions, and a blank space indicates conditions that are optional.

Configuration 1 (CA*SFS*TS) indicates that, in the process of teachers using the artificial intelligence ethics learning chatbot, CA serves as a peripheral condition providing support, while SFS and TS act as

core conditions playing a critical role. This suggests that when the system functions are stable and technical support is adequate, the accuracy of the content enhances teachers' trust in the chatbot and their intention to use it. Therefore, Configuration 1 can be labeled as "Technological quality satisfaction type". The consistency of this configuration is 0.918, with a raw coverage of 0.664 and unique coverage of 0.026. This means that this combinational path can explain 66.4% of the cases related to teachers' intention to accept the chatbot, and 2.6% of the cases can be exclusively explained by this path.

Configuration 2 (SFS*PEU*PU) suggests that, during the use of the artificial intelligence ethics learning chatbot, SFS and PEU play core roles, while PU serves as a peripheral condition offering supplementary support. This implies that when the chatbot's system functionality is stable and teachers find the chatbot easy to use, although perceived usefulness is not a decisive factor, it still helps to some extent in enhancing teachers' intention to use the chatbot. Thus, Configuration 2 can be named "System experience satisfaction type". The consistency of this configuration is 0.906, with a raw coverage of 0.744 and unique coverage of 0.084. This indicates that the combinational path can explain 74.4% of the cases regarding teachers' intention to accept the chatbot, and 8.4% of the cases can be independently explained by this path.

Configuration 3 (~ CA*SFS*~PEU*~PU) shows that, in the process of using the artificial intelligence ethics learning chatbot, SFS serves as the sole core condition playing a crucial role. This suggests that when the chatbot's system functionality is stable, the absence of other conditions does not significantly affect teachers' intention to use the chatbot. The stability of the system itself provides teachers with confidence and assurance to continue using the chatbot. Therefore, Configuration 3 can be labeled as "Functionality stability satisfaction type". The consistency of this configuration is 0.860, with a raw coverage of 0.397 and unique coverage of 0.023. This means that this combinational path can explain 39.7% of the cases related to teachers' intention to accept the chatbot, and 2.3% of the cases can be independently explained by this path.

Configuration 4 (~ CA*~SFS*~TS*PEU*~PU) indicates that, in the process of using the chatbot, PEU serves as the sole core condition playing a key role. This suggests that when teachers perceive the chatbot as easy to operate, the absence of other conditions does not significantly influence their intention to use it. The chatbot's ease of use alone is sufficient to motivate teachers to continue using it. Thus, Configuration 4 can be labeled as "Operational convenience satisfaction type". The consistency of this configuration is 0.914, with a raw coverage of 0.293 and unique coverage of 0.008. This implies that this combinational path can explain 29.3% of the cases related to teachers' intention to accept the chatbot, and 0.8% of the cases can be exclusively explained by this path.

Configuration 5 (~ CA*~SFS*TS*~PEU*PU) suggests that, during the use of the chatbot, SFS acts as a core condition, while PU serves as a peripheral condition providing auxiliary support. This implies that when the system functionality is stable, teachers' perceived usefulness of the chatbot will further enhance their intention to use it. Therefore, Configuration 5 can be labeled as "System value satisfaction type". The consistency of this configuration is 0.936, with a raw coverage of 0.325 and unique coverage

of 0.002. This indicates that the combinational path can explain 32.5% of the cases related to teachers' intention to accept the chatbot, and 0.2% of the cases can be explained by this path.

Conclusion, implications and limitations

This study integrates the TAM with a mixed-methods approach, combining PLS-SEM and fsQCA, to uncover the diverse factors influencing teachers' intention to continue using the chatbot. Based on data from 142 participants, PLS-SEM results indicate that perceived usefulness significantly and positively impacts behavioral intention, while perceived ease of use does not show a significant direct effect. Further fsQCA analysis identifies five sufficient configurations leading to high intention to continue use: Technological quality satisfaction, system experience satisfaction, functionality stability satisfaction, operational convenience satisfaction, and system value satisfaction. These findings highlight the multidimensional nature of technology acceptance in AI ethics education and offer empirical evidence and practical implications for the design of effective and AI-supported learning tools.

The results of the PLS-SEM analysis showed that perceived usefulness had a significant positive impact on teachers' behavioral intention to use the chatbot. This finding is consistent with previous research on continued use intention of information systems (Daneji et al., 2019; Huang, 2019). Foroughi et al. (2023) further pointed out that in educational contexts, perceived usefulness is an important driving force for teachers to adopt AI tools, especially when the chatbot can effectively support ethical reasoning and teaching practices. The results indicate that when teachers perceive the chatbot's value in improving their understanding and application of AI ethics, they are more likely to continue using it. In contrast, perceived ease of use had a nonsignificant direct effect on intention to use, which may be attributed to teachers' high overall digital literacy and therefore their lower sensitivity to usability barriers (Amhag et al., 2019; Saxena & Doleck, 2023). Ngo et al. (2024) further point out that in scenarios with high cognitive load, functional value is often more influential than ease of use in technology adoption. In terms of external factors, content accuracy and system function significantly improve perceived usefulness and perceived ease of use, indicating that information reliability and technical performance are the basis for shaping user value perception. For example, in AI-driven assistance systems, teachers are often more willing to tolerate a certain level of operational complexity as long as the system has substantial benefits in teaching (Gârdan et al., 2025). This result aligns with the research of Fan and Jiang (2024), who found similar patterns in their study of AI-assisted learning tools. Conversely, while technical support has a positive effect on perceived ease of use, it has no significant effect on perceived usefulness. This may be because teachers pay more attention to the chatbot's professional capabilities and autonomous problem-solving characteristics rather than relying on external support services.

This study has several limitations that should be acknowledged. First, the relatively small sample size may limit the representativeness and diversity of the findings, making it difficult to capture the full range of teachers' perceptions and acceptance across different educational levels, subject backgrounds, or institutional settings. Second, the LLM-based chatbot used in this study is still in its early developmental stage, with system instability and incomplete functionality—such as interface issues and delayed

responses—which may have interfered with participants' experiences and affected their actual acceptance and usage behaviors. Third, as most participants were from economically developed regions, the sample may carry regional and cultural biases, reducing the extent to which the findings reflect the perspectives of educators in more diverse socioeconomic and cultural contexts. Fourth, although the study employed a mixed-methods approach incorporating both PLS-SEM and fsQCA, the qualitative interpretation derived from fsQCA configurations may lack depth due to the absence of complementary narrative data (e.g., interviews or open-ended responses). Without richer contextual insights from participants, the configurational findings—though informative—may not fully capture the underlying rationale or motivational reasoning behind teachers' behavioral intentions.

Building on the insights of this study, future research should consider several avenues for further exploration. First, expanding the sample to include a larger and more demographically diverse population, particularly teachers from underrepresented or rural regions, could provide a more nuanced and generalizable understanding of the factors influencing acceptance of AI ethics tools. Second, further technical development of the chatbot is essential. Future studies could assess the impact of specific chatbot improvements, such as adaptive learning features, multimodal interaction, or real-time feedback, on user satisfaction and learning outcomes. Third, cross-cultural or cross-regional comparative studies would be valuable in uncovering how contextual variables, such as cultural attitudes toward AI, policy environments, or institutional readiness, influence ethical AI adoption in education. Longitudinal designs could also offer insights into the sustained impact and evolving perceptions of AI-integrated teaching tools over time. Fourth, to enhance the explanatory power of fsQCA findings, future studies could incorporate qualitative interviews or case studies to triangulate results and provide deeper, context-rich interpretations of teachers' acceptance patterns and ethical reasoning.

Declarations

Ethical Approval Statement

This research protocol was approved by the Research Ethics Committee of the Graduate Institute, Wenzhou University (approval number: WZU-2025-0930C, approval date: September 30, 2025), and all procedures comply with the requirements of the Declaration of Helsinki.

Informed consent statement

All subjects signed a written informed consent form between October 15 and October 22, 2025, and voluntarily participated after fully understanding the purpose, procedures, risks and rights of the study.

Data Availability

The datasets generated during this study are fully available within the article and supplementary materials, which include the post-test questionnaire data on teachers' usage of the LLM-based chatbot. The supplementary files provide the raw dataset with basic coding applied.

Author Contribution

Chenchen Liu contributed to the Resources, Supervision, Funding acquisition, and Writing - Review & Editing. Yangying Yi contributed to the Conceptualization, Methodology, Formal analysis, Writing - Original Draft, and Writing - Review & Editing. Xinying Wang contributed to the Investigation, Data Curation, Writing - Original Draft, and Writing - Review & Editing. Haijie Wang contributed to the Conceptualization, Writing - Original Draft, and Writing - Review & Editing. Youmei Wang contributed to the Resources, Supervision, Project administration, and Writing - Review & Editing.

References

1. Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the technology acceptance model (TAM) to Predict University Students' intentions to use metaverse-based learning platforms. *Education and Information Technologies, 28*(11), 15381-15413. https://doi.org/ 10.1007/s10639-023-11816-3
2. Al-Adwan, A. S., Nofal, M., Akram, H., Albelbisi, N. A., & Al-Okaily, M. (2022). Towards a Sustainable Adoption of E-Learning Systems: The Role of Self-Directed Learning. *Journal of Information Technology Education: Research, 21*. https://doi.org/10.28945/4980
3. Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology Acceptance Model in M-learning context: A systematic review. *Computers & Education, 125*, 389-412. https://doi.org/10.1016/j.compedu.2018.06.008
4. Aljuaid, H. (2024). The impact of artificial intelligence tools on academic writing instruction in higher education: A systematic review. *Arab World English Journal (AWEJ) Special Issue on ChatGPT*, 26-55. https://dx.doi.org/10.24093/ awej/ChatGPT.2
5. Almaiah, M. A., & Al Mulhem, A. (2019). Analysis of the essential factors affecting of intention to use of mobile learning applications: A comparison between universities adopters and non-adopters. *Education and Information Technologies,24*(2),1433-1468.https://doi.org/10.1007/ s10639-018-9840-1
6. Almaiah, M. A., & Alamri, M. M. (2018). Proposing a new technical quality requirements for mobile learning applications. *Journal of Theoretical and Applied Information Technology, 96*(19), 6955-6968.
7. Almaiah, M. A., Jalil, M. A., & Man, M. (2016). Extending the TAM to examine the effects of quality features on mobile learning acceptance. *Journal of Computers in Education, 3*, 453-485.https://doi.org/10.1007/s40692-016-0074-1
8. Almuhanna, M. A. (2024). Teachers' perspectives of integrating AI-powered technologies in K-12 education for creating customized learning materials and resources. *Education and Information Technologies*, 1-29.https://doi.org/ 10.1007/s10639-024-13257-y
9. Amhag, L., Hellström, L., & Stigmar, M. (2019). Teacher Educators' Use of Digital Tools and Needs for Digital Competence in Higher Education. *Journal of Digital Learning in Teacher Education, 35*(4),

203–220. https://doi.org/10.1080/21532974.2019.1646169

10. Arteaga Sánchez, R., Duarte Hueros, A., & García Ordaz, M. (2013). E-learning and the University of Huelva: a study of WebCT and the technological acceptance model. *Campus-Wide Information Systems, 30*(2), 135-160. https://doi.org/10.1108/ 10650741311306318
11. Ayanwale, M. A., Adelana, O. P., Molefi, R. R., Adeeko, O., & Ishola, A. M. (2024). Examining artificial intelligence literacy among pre-service teachers for future classrooms. *Computers and education open, 6*(1)..https://doi.org/10.1016/j.caeo. 2024.100179
12. Baek, T. H., & Kim, M. (2023). Is chatgpt scary good? How user motivations affect creepiness and trust in generative artificial intelligence. *Telematics and Informatics, 83*(3). https://doi.org/ 10.1016/j.tele.2023.102030
13. Bai, B., Wang, J., & Chai, C. S. (2021). Understanding Hong Kong primary school English teachers' continuance intention to teach with ICT. *Computer Assisted Language Learning, 34*(4), 528-551. https://doi.org/10.1080/09588221.2019. 1627459
14. Bakar-Corez, A., & Kocaman-Karoglu, A. (2024). E-dishonesty among postgraduate students and its relation to self-esteem. *Education and Information Technologies, 29*(7), 8275-8300. https:// doi.org/10.1007/s10639-023-12105-9
15. Barrett, A. J., Pack, A., & Quaid, E. D. (2021). Understanding learners' acceptance of high-immersion virtual reality systems: Insights from confirmatory and exploratory PLS-SEM analyses. *Computers & Education, 169*(81). https:// doi.org/10.1016/j.compedu.2021.104214
16. Belda-Medina, J., & Calvo-Ferrer, J. R. (2022). Using Chatbots as AI Conversational Partners in Language Learning. *Applied Sciences, 12*(17), 8427. https://doi.org/ 10.3390/app12178427
17. Bozkurt, A. (2023). Generative artificial intelligence (AI) powered conversational educational agents: The inevitable paradigm shift. *Asian Journal of Distance Education, 18*(1), 198-204.https:// doi.org/10.5281/zenodo.7716416
18. Cheng, Y. M. (2012). Effects of quality antecedents on e-learning acceptance. *Internet Research, 22*(3), 361-390.https://doi.org/10.1108/10662241211235699
19. Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern methods for business research, 295*(2), 295-336.
20. Daneji, A. A., Ayub, A. F. M., & Khambari, M. N. M. (2019). The effects of perceived usefulness, confirmation and satisfaction on continuance intention in using massive open online course (MOOC). *Knowledge Management & E-Learning, 11*(2), 201-214.https://doi.org/10.34105/ j.kmel.2019.11.010
21. 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.https://doi.org/ 10.1287/mnsc.35.8.982
22. DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research, 38*(6), 373–384.https:// doi.org/10.1287/isre.3.1.60

23. DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A 10-year update. *Journal of Management Information Systems, 19*(4),9–30.https://doi.org/10.1080/07421222.2003.11045748
24. Du, W., Liang, R. Y., & Liu, D. (2022). Factors influencing school teachers' continuous usage intention of using VR technology for classroom teaching. *Sage Open, 12*(3). https://doi.org/10.1177/21582440221114325
25. Dwivedi, Y. K., Wade, M. R., & Schneberger, S. L. (Eds.). (2011). Information systems theory: Explaining and predicting our digital society, vol. 1. https://doi.org/ 10.1007/978-1-4419-6108-2
26. Eke, D. O. (2023). Chatgpt and the rise of generative AI: Threat to academic integrity? *Journal of Responsible Technology, 13*.https://doi.org/10.1016/j.jrt. 2023.100060
27. Farhan, W., Razmak, J., Demers, S., & Laflamme, S. (2019). E-learning systems versus instructional communication tools: Developing and testing a new e-learning user interface from the perspectives of teachers and students. *Technology in Society, 59.* https://doi.org/10.1016/j.techsoc.2019.101192.
28. Fornell, C. & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research 18*, 39-50.https://doi.org/10.1177/002224378101800104
29. Gajic, N., & Boolaky, M. (2015). Impact of technical support on customer satisfaction: Case of automotive paints. *SAGE Open, 5*(4).https://doi.org/10.1177/2158244 015611457
30. Gârdan, I. P., Manu, M. B., Gârdan, D. A., Negoiță, L. D. L., Paștiu, C. A., Ghiță, E., & Zaharia, A. (2025, February). Adopting AI in education: optimizing human resource management considering teacher perceptions. *In Frontiers in Education, 10*. https://doi.org/10.3389/feduc. 2025.1488147
31. Ghavifekr, S., & Rosdy, W. A. W. (2015). Teaching and learning with technology: Effectiveness of ICT integration in schools. *International journal of research in education and science, 1*(2), 175-191.https://doi.org/10.21890/ijres.23596
32. Giang, N. T. T., & Nga, P. T. H. (2024). The influence of information systems on student satisfaction: A study of perceived ease of use and perceived usefulness. *Journal of Financial-Marketing Research, 15*(2), 62-72. https://doi.org/10.52932/jfm.vi2. 479
33. Gómez-Ramirez, I., Valencia-Arias, A., & Duque, L. (2019). Approach to M-learning acceptance among university students: An integrated model of TPB and TAM. *International Review of research in open and distributed learning, 20*(3).https://doi.org/10.19173/irrodl.v20i4.4061 CopiedAn error has occu
34. Grönroos, C. (1984). A service quality model and its marketing implications. *European Journal of marketing, 18*(4), 36-44.https://doi.org/10.1108/EUM0000000004784
35. Hagendorff, T. (2020). The ethics of AI ethics: An evaluation of guidelines. *Minds and machines, 30*(1), 99-120.https://doi.org/10.1007/s11023-020-09517-8
36. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squaresstructural equation modeling (PLS-SEM). *International Journal of Research & Method in*

Education, 38(2), 220–221.https://doi.org/10.1080/ 1743727X.2015.1005806

37. Han, J. H., & Sa, H. J. (2022). Acceptance of and satisfaction with online educational classes through the technology acceptance model (TAM): The COVID-19 situation in Korea. *Asia Pacific Education Review, 23*(3), 403-415.https:// doi.org/10.1007/s12564-021-09716-7
38. Hsu, L. (2016). Examining EFL teachers' technological pedagogical content knowledge and the adoption of mobile-assisted language learning: a partial least square approach. *Computer Assisted Language Learning, 29*(8), 1287–1297. https://doi.org/10.1080/09588221.2016.1278024
39. Hu, H. H., Kandampully, J., & Juwaheer, T. D. (2009). Relationships and impacts of service quality, perceived value, customer satisfaction, and image: an empirical study. *The service industries journal, 29*(2), 111-125.https://doi.org/10.1080/ 02642060802292932
40. Hu, Y. H. (2022). Effects and acceptance of precision education in an AI-supported smart learning environment. *Education and Information Technologies,27*(2),2013-2037.https://doi.org/10.1007/s10639-021-10664-3
41. Huang, Y. M. (2019). Examining students' continued use of desktop services: Perspectives from expectation-confirmation and social influence. *Computers in Human Behavior, 96*, 23-31.https://doi.org/10.1016/j.chb.2019.02.010
42. Ibrahim, A., & Shiring, E. (2022). The Relationship between Educators' Attitudes, Perceived Usefulness, and Perceived Ease of Use of Instructional and Web-Based Technologies: Implications from Technology Acceptance Model (TAM). *International Journal of Technology in Education, 5*(4), 535-551.https:// doi.org/10.46328/ijte.285
43. Ipek, Z. H., Gozum, A. C., Papadakis, S., & Kallogianakis, M. (2023). Educational applications of the ChatGPT AI system: A systematic review research. Educational Process. *International Journal, 12*(3), 26–55.https://doi.org/ 10.22521/edupij.2023.123.2
44. Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature machine intelligence, 1*(9), 389-399. https://doi.org/10.1038/s42256-019-0088-2
45. Kalankesh, L. R., Nasiry, Z., Fein, R. A., & Damanabi, S. (2020). Factors influencing user satisfaction with information systems: a systematic review. *Galen Medical Journal, 9*. https://doi.org/10.31661/gmj.v9i0.1686.
46. Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and individual differences, 103*.https://doi.org/10.1016/j.lindif.2023.102274
47. Kazim, E., & Koshiyama, A. S. (2021). A high-level overview of AI ethics. *Patterns, 2*(9). https://doi.org/10.1016/j.patter.2021.100314
48. Ke, C. H., Sun, H. M., & Yang, Y. C. (2012). Effects of User and System Characteristics on Perceived Usefulness and Perceived Ease of Use of the Web-Based Classroom Response System. *Turkish Online Journal of Educational Technology, 11*(3), 128-143.https://files.eric.ed.gov/fulltext/EJ989206.pdf

49. Kim, N. J., & Kim, M. K. (2022, March). Teacher's perceptions of using an artificial intelligence-based educational tool for scientific writing. *In Frontiers in education, 7*. https://doi.org/10.3389/feduc.2022.755914
50. Kim, Y., & Lee, H. S. (2014). Quality, perceived usefulness, user satisfaction, and intention to use: An empirical study of ubiquitous personal robot service. *Asian Social Science, 10*(11), 1.https://doi.org/10.5539/ass.v10n11p1
51. King, W., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*, 740-755.https://doi.org/10.1016/j.im.2006. 05.003
52. Leppänen, P., George, G., & Alexy, O. (2023). When do novel business models lead to high performance? A configurational approach to value drivers, competitive strategy, and firm environment. *Academy of management journal, 66*(1), 164-194.https://doi.org/10.5465/amj.2020.0969
53. Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., & Pechenkina, E. (2023). Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators. *The international journal of management education, 21*(2),.https://doi.org/10.1016/j.ijme.2023.100790
54. Liu, I. F., Chen, M. C., Sun, Y. S., Wible, D., & Kuo, C. H. (2010). Extending the TAM model to explore the factors that affect intention to use an online learning community. *Computers & education, 54*(2), 600-610. https://doi.org/10.1016/ j.compedu.2009.09.009
55. Ma, Q., & Liu, L. (2004). The technology acceptance model: A meta-analysis of empirical findings. *Journal of Organizational and End User Computing, 16*(1), 59-72.https://doi.org/10.4018/ 978-1-59140-474-3.ch006
56. Machdar, N. M. (2016). The effect of information quality on perceived usefulness and perceived ease of use. *Business and entrepreneurial review, 15*(2), 131-146. https://doi.org/10.25105/ber.v15i2. 4630
57. Mahande, R. D., Jasruddin, J., & Nasir, N. (2019). Is success model for EDMODO e-learning user satisfaction through TAM on students. *Journal of Educational Science and Technology, 5*(2), 140-152.https://doi.org/10.26858/est.v5i2.9575
58. Mouta, A., Torrecilla-Sánchez, E. M., & Pinto-Llorente, A. M. (2025). Comprehensive professional learning for teacher agency in addressing ethical challenges of AIED: Insights from educational design research. *Education and Information Technologies, 30*(3), 3343-3387.https://doi.org/10.1007/s10639-024-12946-y
59. Nelson, R. R., Todd, P. A., & Wixom, B. H. (2005). Antecedents of information and system quality: an empirical examination within the context of data warehousing. *Journal of management information systems, 21*(4), 199-235. https://doi.org/ 10.1080/07421222.2005.11045823
60. Ngo, T. T. A., Tran, T. T., An, G. K., & Nguyen, P. T. (2024). ChatGPT for educational purposes: Investigating the impact of knowledge management factors on student satisfaction and continuous

usage. *IEEE Transactions on Learning Technologies, 17*, 1367–1378.https://doi.org/10.1109/TLT.2024.3383773

61. Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethical principles for artificial intelligence in education. *Education and information technologies, 28*(4), 4221-4241.
62. Nikolopoulou, K. (2021). Mobile Devices and Mobile Learning in Greek Secondary Education: Policy, Empirical Findings and Implications. *In Handbook for online learning contexts: Digital, mobile and open: Policy and practice* (pp. 67-80). https://doi.org/10.1007/978-3-030-67349-9_6
63. Ohliati, J., & Abbas, B. S. (2019). Measuring students satisfaction in using learning management system. *International Journal of Emerging Technologies in Learning (Online), 14*(4), 180-189. https://doi.org/10.3991/ijet.v14i04.9427
64. Onwuegbuzie, A. J., & Daniel, L. G. (2002). A framework for reporting and interpreting internal consistency reliability estimates. *Measurement and evaluation in counseling and development, 35*(2), 89-103. https://doi.org/10.1080/07481756. 2002.12069052
65. Padayachee, I. (2017). Educator perceptions of virtual learning system quality characteristics. *South African Computer Journal, 29*(3), 95-126. https://hdl. handle.net/10520/EJC-c5c8388c1
66. Pappas, I. O., & Woodside, A. G. (2021). Fuzzy-set Qualitative Comparative Analysis (fsQCA): Guidelines for research practice in Information Systems and marketing. *International Journal of Information Management, 58*. https://doi.org/10.1016/ j.ijinfomgt.2021.102310
67. Patra, I., Alazemi, A., Al-Jamal, D., & Gheisari, A. (2022). The effectiveness of teachers' written and verbal corrective feedback (CF) during formative assessment (FA) on male language learners' academic anxiety (AA), academic performance (AP), and attitude toward learning (ATL). *Language Testing in Asia, 12*(1), 19. https://doi.org/10.1186/s40468-022-00169-2
68. Rai, A., Lang, S. S., & Welker, R. B. (2002). Assessing the validity of IS success models: An empirical test and theoretical analysis. *Information systems research, 13*(1), 50-69.https://doi.org/10.1287/isre.13.1.50.96
69. Rihoux, B., & Ragin, C. C. (2009). Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques. *SAGE Publications, Inc*.https://doi.org/10.4135/9781452226569
70. Scherer, R., Siddiq, F., & Teo, T. (2015). Becoming more specific: Measuring and modeling teachers' perceived usefulness of ICT in the context of teaching and learning. *Computers & Education, 88*, 202-214. https://doi.org/10.1016/j. compedu.2015.05.005
71. Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & education, 128*, 13-35.https://doi.org/10.1016/j.compedu.2018.09.009
72. Seddon, P. B. (1997). A respecification and extension of the DeLone and McLean model of IS success. *Information systems research, 8*(3), 240-253. https://doi.org/ 10.1287/isre.8.3.240

73. Shen, X., & Liu, J. (2022). Analysis of factors affecting user willingness to use virtual online education platforms. *International Journal of Emerging Technologies in Learning, 17*(1), 74-89. https://doi.org/10.3991/ijet.v17i01.28713
74. Siafıs, V., Rangoussi, M., & Psaromiligkos, Y. (2024). Recommender Systems for Teachers: A Systematic Literature Review of Recent (2011–2023) Research. *Education Sciences, 14*(7), 723.https://doi.org/10.3390/educsci14070723
75. Teo, T. (2010). A path analysis of pre-service teachers' attitudes to computer use: applying and extending the technology acceptance model in an educational context. *Interactive Learning Environments, 18*(1), 65-79. https://doi.org/10. 1080/10494820802231327
76. Uddin, M.M. (2024). Rejection or integration of AI in academia: determining the best choice through the Opportunity Cost theoretical formula. *Discover Education, 3*(249).https://doi.org/10.1007/s44217-024-00349-7
77. Waheed, M., & Jam, F. A. (2010). Teacher's intention to accept online education: Extended TAM model. *Interdisciplinary Journal of Contemporary Research in Business, 2*(5), 330-344.
78. Wang, S., Sun, Z., & Chen, Y. (2023). Effects of higher education institutes' artificial intelligence capability on students' self-efficacy, creativity and learning performance. *Education and Information Technologies, 28*(5), 4919–4939. https://doi.org/10.1007/s10639-022-11338-4.
79. Wang, Y., Liu, C., & Tu, Y. F. (2021). Factors affecting the adoption of AI-based applications in higher education. *Educational Technology & Society, 24*(3), 116-129.https://www.jstor.org/stable/27032860
80. Wiese, L. J., Patil, I., Schiff, D. S., & Magana, A. J. (2025). AI Ethics Education: A Systematic Literature Review. *Computers and Education: Artificial Intelligence, 8*. https://doi.org/10.1016/j.caeai.2025.100405
81. Xu, J., Benbasat, I., & Cenfetelli, R. T. (2013). Integrating service quality with system and information quality: An empirical test in the e-service context. *MIS quarterly, 37*(3), 777-794. https://www.jstor.org/stable/43825999
82. Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. *International Journal of Educational Technology in Higher Education, 20*(1), 49.https://doi.org/10.1186/s41239- 023-00420-7
83. Zheng, Y., Zhao, K., & Stylianou, A. (2013). The impacts of information quality and system quality on users' continuance intention in information-exchange virtual communities: An empirical investigation. *Decision support systems, 56*, 513-524.https://doi.org/10.1016/j.dss.2012.11.008

Figures

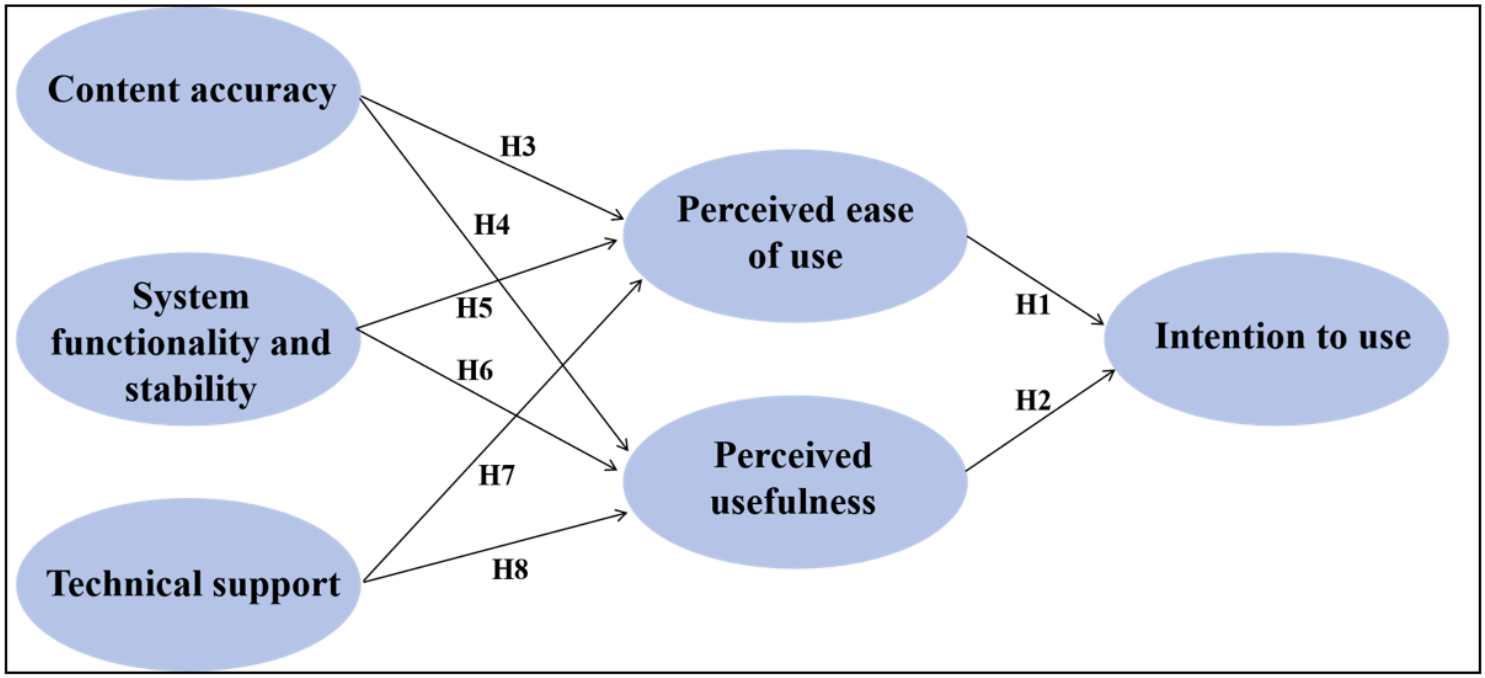


Figure 1

Theoretical confirmatory model

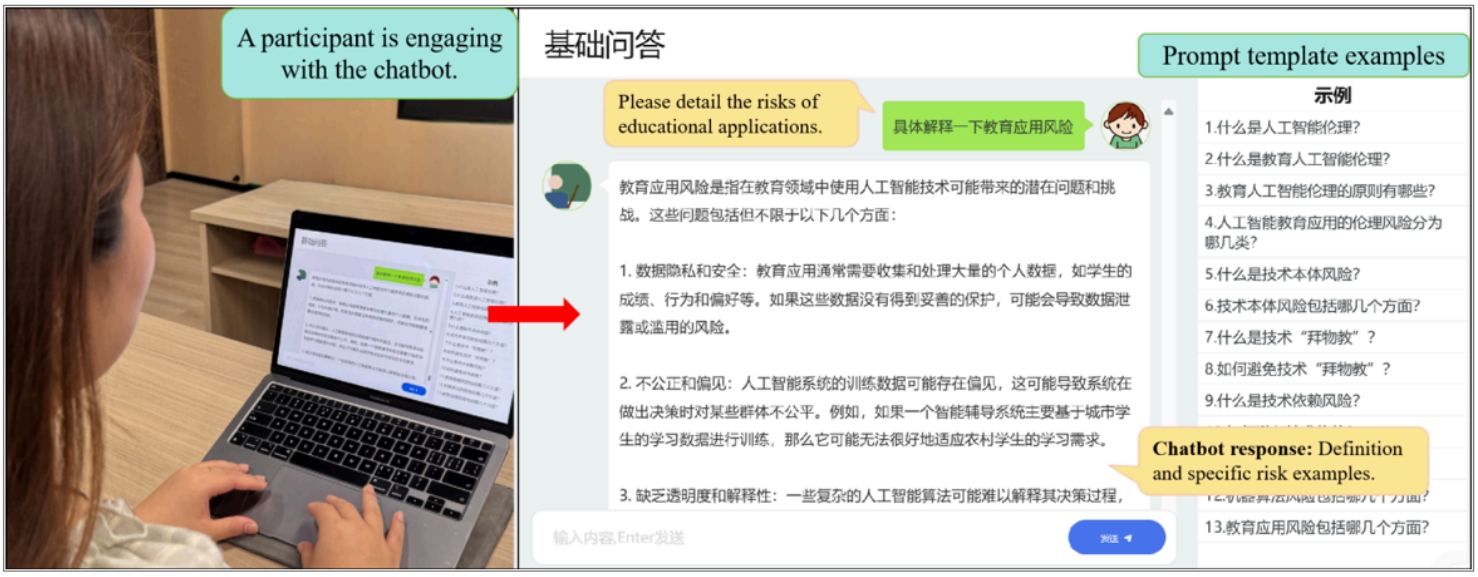


Figure 2

Learning interface of the chatbot.

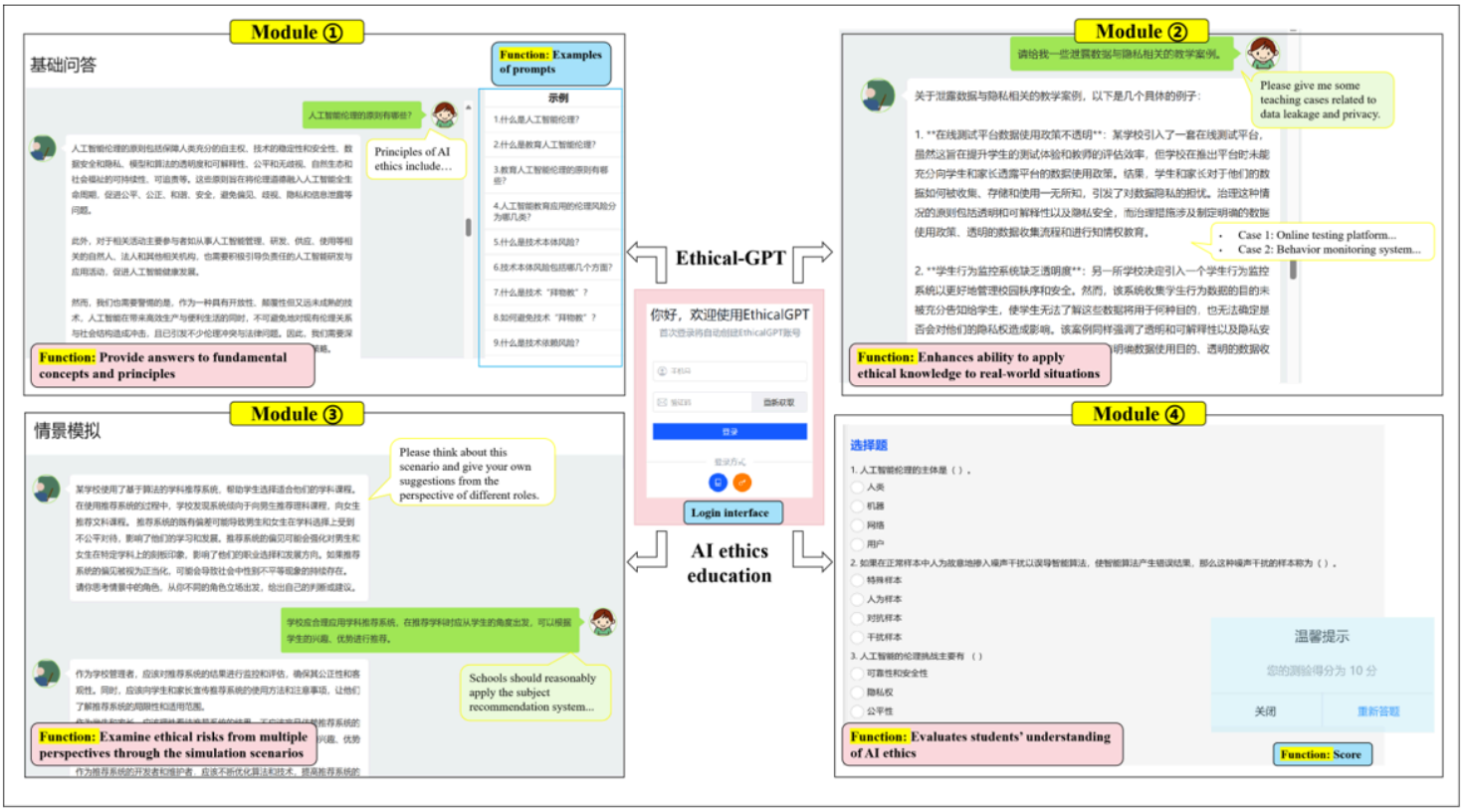


Figure 3

The modules and functions of the chatbot

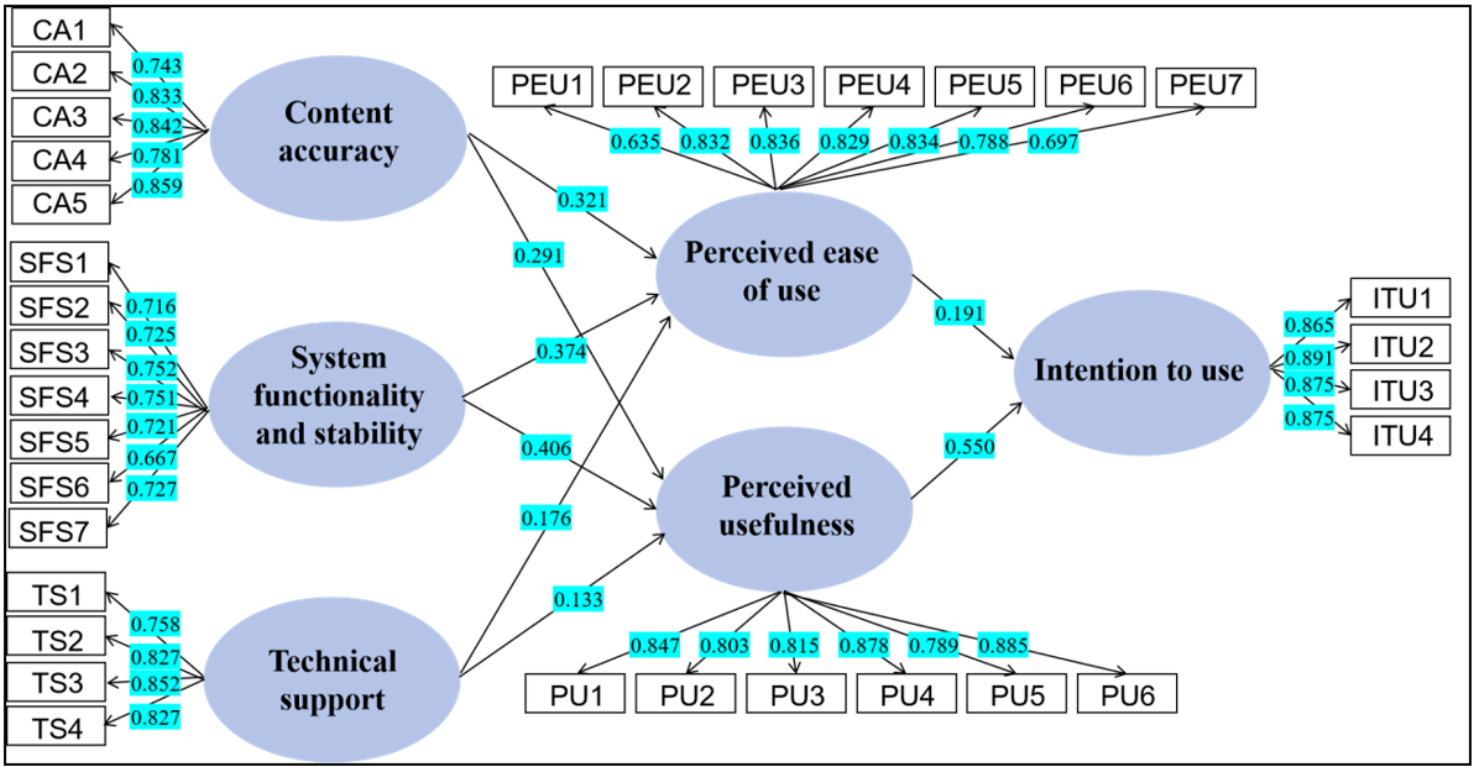


Figure 4

Confirmatory model results

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- RawDataset.xlsx