Brain, Digital, & Learning

pISSN : 2384-2474
eISSN : 2586-7490

RESEARCH ARTICLE

Exploring the Structural Relations Influencing K-12 Teachers' Acceptance of Generative AI in Education: An Application of the UTAUT Model

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ABSTRACT

This study applied the unified theory of acceptance and use of technology (UTAUT) model to examine the structural relations among performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and actual use of generative AI in education among K-12 teachers. It also investigated the moderating roles of gender, age, professional development experience, and daily use experience. Survey data were collected from 347 K-12 teachers in South Korea. Structural equation modeling was employed to test the hypothesized relations, and multi-group analyses were conducted to examine group differences in associations across teacher subgroups. The results revealed that performance expectancy ($\beta = .76$, $p < .001$) was the factor most strongly associated with teachers' behavioral intention to use generative AI in education. Social influence and facilitating conditions also showed significant positive associations in the overall model, whereas effort expectancy did not. However, effort expectancy showed a meaningful association among teachers aged 40 and above, as well as those with limited professional development or limited daily use experience. Moreover, behavioral intention significantly predicted actual use both directly and indirectly, mediating the effects of performance expectancy and facilitating conditions. This study extends the UTAUT framework by empirically validating teacher acceptance of generative AI in the K-12 educational context. The findings provide theoretical insights into technology acceptance mechanisms and offer practical and policy implications for effectively integrating generative AI into classroom teaching.

Keywords: Generative AI in education, UTAUT model, K-12 teachers, technology integration

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Brain, Digital, & Learning
2025, Vol. 15, No. 4, 533-554
https://doi.org/10.31216/BDL.2025.15.4.1

Received: December 02, 2025
Revised: December 15, 2025
Accepted: December 15, 2025

Introduction

The emergence of generative artificial intelligence (GenAI) has brought unprecedented possibilities and challenges to K-12 education. Unlike conventional AI, which is primarily used for analyzing and predicting data based on predefined rules, GenAI can create novel content-text, images, videos, and code-enabling it to transform educational paradigms (Agbo et al., 2025;

Marzano, 2025). Such generative capabilities enable diverse pedagogical innovations, including personalized learning experiences, instant feedback, automated lesson design and material creation, and the development of assessment items (Cheah & Kim, 2025; Gunsaldi et al., 2025). However, the integration of GenAI into education entails not only opportunities but also significant risks. While it can enhance self-directed learning and alleviate teachers' workload, concerns remain regarding the accuracy of generated information, algorithmic bias, plagiarism and unethical use, data privacy, and excessive reliance on AI (Alavi et al., 2024; Bastani et al., 2024; Farrelly & Baker, 2023; Lee & Kim, 2025). Given these dual possibilities, teachers' professional judgment and active acceptance are critical prerequisites for ensuring the pedagogical effectiveness and trustworthiness of GenAI in education.

With its increasing utility across scientific, cultural, and industrial domains, GenAI is rapidly spreading worldwide, necessitating the development of competencies that enable collaboration with AI technologies (Ng et al., 2023; Roose, 2022; Zhung et al., 2024). Thus, teaching with GenAI in K-12 contexts extends beyond mere technological adoption; it represents an educational endeavor to equip students with essential skills for the future (Lee & Kim, 2025; Song et al., 2025). Teachers' positive perceptions and voluntary acceptance are, therefore, crucial determinants of the successful integration of GenAI into classroom practice (Kim & Lee, 2021; Teo, 2011).

Despite the importance of teacher acceptance, research systematically examining the structural factors that influence K-12 teachers' perceptions and actual use of GenAI remains limited. The technology acceptance model (TAM; Davis, 1989) has been widely used to explain users' technology adoption in education, yet it has been criticized for its limited capacity to account for contextual and social influences, and for focusing only on behavioral intention rather than actual use (Gangwar et al., 2014; Lim, 2018). To overcome these limitations, the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) integrates performance expectancy, effort expectancy, social influence, and facilitating conditions, providing a more comprehensive framework for predicting both behavioral intention and actual use.

Accordingly, the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh and colleagues (2003) has become a prominent theoretical framework for more comprehensively explaining not only users' intentions to accept a technology but also their actual use behavior, by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions as core determinants. For this reason, educational technology research has continuously employed UTAUT to examine the structural mechanisms underlying students' and teachers' acceptance intentions and actual technology use (e.g., Aliyu et al., 2019; Almaiah et al., 2019; Bower et al., 2020; Kim & Lee, 2022; Zhang & Wareewanich, 2024).

However, because GenAI operates in ways that differ from conventional technologies, it isn't easy to assume that UTAUT constructs function in the same manner in the GenAI context. Unlike traditional ICT- or LMS-based technologies, GenAI may impose new cognitive and ethical burdens on users, including unpredictable outputs, hallucinations, biased responses, plagiarism and copyright concerns, and the potential for unethical use (Reihanian et al., 2024; Song et al., 2025). For example, although GenAI's natural language interface may appear easy to use, interpreting and validating generated outputs requires additional cognitive effort and accountability, suggesting the need to reconceptualize effort expectancy. Performance expectancy may likewise exhibit a dual structure in which expectations for expanding teaching and learning experiences and improving efficiency coexist with concerns about inaccuracies and plagiarism. Reflecting these characteristics, prior research has reported that teachers tend to form ambivalent and complex attitudes toward the educational use of GenAI.

Building on this theoretical foundation, the present study extends the UTAUT model to examine the mechanisms underlying K-12 teachers' acceptance of GenAI in education. Specifically, this study aims to (1) test the structural relations among performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and actual use; (2) examine the mediating role of behavioral intention in linking antecedent factors to actual use; and (3) explore the moderating roles of teachers' demographic and experiential characteristics-including gender, age, professional development experience, and daily use experience. Through these objectives, the study seeks to extend the theoretical understanding of teacher acceptance of GenAI and provide empirical insights for designing teacher training programs and institutional support systems that facilitate effective AI integration in K-12 classrooms.

Literature Review

Generative AI in Education

GenAI in education refers to an instructional approach that employs artificial intelligence capable of generating various types of output-such as text, images, audio, videos, and code-in response to large datasets or user-entered prompts, thereby supporting teaching and learning processes (Lee & Kim, 2025). GenAI enables interactive communication through natural-language processing, flexibly responding to learners' questions and requests without topical or contextual constraints. It can also produce creative ideas and learning resources in diverse formats within a short period, functioning as a versatile pedagogical aid (Moundridou et al., 2024; Tlili et al., 2023).

In the K-12 context, GenAI has been increasingly integrated with various instructional strategies across subject areas. For example, Chen et al. (2025) found that a GenAI-based system in history education enhanced students' knowledge acquisition and learning motivation while reducing cognitive load. Meşe et al. (2025) reported that the application of ChatGPT in English education promoted learners' cognitive and emotional engagement. Similarly, Song et al. (2025) demonstrated that creative mathematics writing activities supported by GenAI improved students' mathematical understanding and problem-solving abilities.

Still, some researchers have raised concerns about the pedagogical use of GenAI. When integrated into classroom teaching, GenAI may encourage the uncritical acceptance of incorrect information, diminish authentic learning opportunities, and, in the long term, worsen learning outcomes, reduce motivation and engagement, weaken critical-thinking skills, and foster an overreliance on AI technologies (Bastani et al., 2024; Forero & Herrera-Suarez, 2023; Oğuz Haçat & Kepceoğlu, 2025; Song et al., 2025; Warschauer et al., 2023; Wecks et al., 2024). Accordingly, pedagogical strategies for using GenAI safely should aim to retain its positive effects-such as increased efficiency, personalization, creativity support, and immediate feedback-while incorporating safeguards, including the design of critical-thinking tasks, structured learning activities, and explicit instruction in AI ethics (Lee & Kim, 2025).

Notably, the effective use of GenAI in educational settings requires K-12 teachers to be able to adapt and reconstruct technology in ways that align with instructional goals and learner characteristics, reflecting a technological pedagogical content knowledge perspective (Celik, 2023). If teachers rely on GenAI merely as a mechanical tool without pedagogical alignment, they may fail to mitigate its negative consequences and realize its expected educational benefits (Tan et al., 2025). Therefore, K-12 teachers' acceptance of GenAI in education should be understood as a complex phenomenon shaped by the interplay among perceived educational usefulness, perceived ease of use, social influence, and teachers' demographic and experiential factors (Dindar, 2021; Kamsin, 2025; Wang et al., 2025).

To systematically explain these interrelations, the present study employs the UTAUT as a robust theoretical framework to analyze the structural mechanisms underlying K-12 teachers' acceptance of GenAI in education.

Integrated Technology Acceptance Models in Education

For several decades, research on technology adoption in education has evolved through various theoretical frameworks such as the TAM and the UTAUT (Granić & Marangunić, 2019; Khechine et al., 2016; Kittinger & Law, 2024). The TAM proposed by Davis (1989) has been widely applied to explain users' behavioral intentions toward technology use by identifying perceived usefulness and perceived ease of use as key determinants. To address the limitations of TAM, Venkatesh et al. (2003) integrated multiple earlier theories, including the theory of reasoned action, TAM, and social cognitive theory, to develop the UTAUT model. This model established performance expectancy, effort expectancy, social influence, and facilitating conditions as core constructs that collectively predict users' behavioral intention and actual use of technology. Furthermore, the UTAUT posits that the effects of these constructs are moderated by demographic and experiential variables such as gender, age, experience, and voluntariness of use (Venkatesh et al., 2003).

Since its introduction, the UTAUT model has been extensively applied in educational settings to explain students' and instructors' technology adoption behaviors. For example, Tosuntaş et al. (2015) applied the UTAUT to interactive whiteboards, Olasina (2019) to e-learning, Wang et al. (2009) and Almaiah et al. (2019) to mobile learning, Aliyu et al. (2019) to Moodle-based learning systems, Kim and Lee (2022) to ICT-based instruction, Bower et al. (2020) to immersive virtual environments, and Kim and Lee (2021) and Zhang and Wareewanich (2024) to AI-enhanced education. These studies consistently demonstrated that UTAUT provides strong predictive power for exploring users' behavioral intention mechanisms across diverse educational technologies.

Across different educational technology contexts, UTAUT-based studies have consistently identified performance expectancy as the most potent predictor of behavioral intention (Kittinger & Law, 2024). For instance, Almaiah et al. (2019) reported that performance expectancy had a significant positive influence on behavioral intention toward mobile learning systems, while Kim and Lee (2021) found that performance expectancy was the key determinant of elementary teachers' acceptance of AI-based instruction. By contrast, findings regarding effort expectancy have been mixed. Wang et al. (2009) found that effort expectancy significantly influenced behavioral intention toward mobile learning, whereas other studies reported statistically insignificant effects (Kim & Lee, 2021; Pynoo et al., 2011). Similarly, the influence of social influence has varied depending on context: Aliyu et al. (2019) found a significant positive effect on students' acceptance of Moodle systems, while Teo (2011) and Kim and Lee (2022) found no significant relation. The results for facilitating conditions have also been inconsistent. Some studies (e.g., Almaiah et al., 2019; Kim & Lee, 2021; Teo, 2011) found that facilitating conditions indirectly affected actual use through behavioral intention, whereas others (e.g., Arasanm et al., 2017; Pynoo et al., 2011) reported minimal direct influence on actual behavior. Such inconsistent findings suggest that the strength and direction of UTAUT constructs' effects vary according to the specific technological context and user characteristics, underscoring the need to revalidate the model in the emerging context of GenAI in education.

Furthermore, GenAI is structurally distinct from conventional ICT tools and LMS-based technologies, suggesting that the technology acceptance mechanism itself may operate differently. Unlike traditional technologies that perform predefined functions and yield relatively predictable outcomes, GenAI generates outputs that can be unpredictable depending on users' inputs, requiring users to continuously verify the accuracy, reliability, and potential bias of the results (Reihanian et al., 2024; Song et al., 2025). In this process, although GenAI may appear easy to use on the surface due to its natural language interface, users must also monitor and calibrate issues such as hallucinations, biased responses, plagiarism, copyright concerns, and the potential for unethical use, thereby incurring new cognitive burdens. Therefore, in the educational use of GenAI, effort expectancy should be reinterpreted beyond simple ease of use to encompass the cognitive and ethical effort required for responsible use. Performance expectancy may likewise take the form of a dual expectation structure, in which anticipated gains in learning efficiency and emergent outcomes coexist with uncertainty about generated outputs, plagiarism risks, and assessment ambiguity. Moreover, prior work has reported that teachers recognize both the educational opportunities and potential dangers of GenAI, exhibiting a complex attitudinal structure in which divergent perceptions coexist rather than a simple positive–negative ambivalence. Taken together, these characteristics suggest that the exact mechanisms of conventional technologies cannot fully explain GenAI acceptance, and they underscore the need to empirically examine how core UTAUT constructs are reconfigured and interact within the GenAI context.

Although prior studies have extensively examined teachers' behavioral intention and actual use of various educational technologies, systematic research on the mechanisms underlying K-12 teachers' acceptance of GenAI is still nascent. Accordingly, this study applies the UTAUT model to analyze the structural relations among the factors associated with K-12 teachers' acceptance of GenAI in education-specifically, how performance expectancy, effort expectancy, social influence, and facilitating conditions relate to actual use both directly and indirectly through behavioral intention. In this study's context, performance expectancy refers to the extent to which teachers believe that using GenAI in education will enhance instructional performance and efficiency; effort expectancy denotes teachers' perceptions of the ease and convenience of using GenAI technologies; social influence captures the perceived pressure or encouragement from significant referents (e.g., colleagues, school administrators) to use GenAI; and facilitating conditions reflect teachers' perceptions of the adequacy of technical and organizational infrastructure supporting the educational use of GenAI.

Teachers' Characteristics and Technology Acceptance

In addition to the primary constructs of the UTAUT model, teachers' demographic and experiential characteristics play a crucial role in shaping their acceptance of technology. The UTAUT framework posits that variables such as gender, age, and experience act as moderators that influence the strength and direction of relations among core constructs (Venkatesh et al., 2003). This implies that the effects of factors such as performance expectancy and effort expectancy are not uniform across all teachers but vary depending on individual characteristics and contextual differences.

Previous studies have provided empirical evidence for these moderating effects in educational settings. For instance, Tosuntaş et al. (2015) reported that effort expectancy was a more salient determinant of behavioral intention among female teachers than male teachers. In contrast, a meta-analysis by Scherer and Teo (2019) found no consistent gender differences across multiple countries.

Age has also been identified as a significant factor: Pynoo et al. (2011) found that effort expectancy had a more substantial influence on older teachers, while O'Bannon and Thomas (2014) observed that senior teachers encountered greater barriers and displayed lower digital efficacy when integrating mobile devices into instruction. Similarly, Dindar et al. (2021) compared teachers' experiences with learning management systems during the COVID-19 pandemic. They revealed that effort expectancy was a stronger predictor of behavioral intention among less experienced teachers, whereas performance expectancy played a more dominant role among experienced teachers. In addition, Kim and Lee (2021) demonstrated that teachers with extensive professional development experience and daily use experience with AI technologies were more substantially impacted by social influence and facilitating conditions than those with lesser experience.

The UTAUT model has demonstrated a relatively high explanatory power-approximately 70% of the variance in behavioral intention-surpassing earlier acceptance models (Khechine et al., 2016; Venkatesh et al., 2003). Nevertheless, prior research indicates that the magnitude and significance of the effects of performance expectancy, effort expectancy, social influence, and facilitating conditions on behavioral intention and actual use vary depending on the type of technology, user group, and contextual factors such as gender, teaching experience, and grade level taught. These findings underscore the importance of contextualizing the UTAUT framework when applied to educational environments (Khechine et al., 2016; Venkatesh et al., 2003). In this regard, empirically verifying whether similar moderating patterns emerge in the context of GenAI in education is necessary.

Accordingly, this study argues that understanding K-12 teachers' acceptance of GenAI requires not only examining the relations between performance expectancy, effort expectancy, social influence, and facilitating conditions, but also considering how these relations differ by gender, age, professional development experience, and daily use experience. Such an integrative approach enables the identification of differentiated support strategies and policy implications tailored to distinct teacher subgroups. Building on this perspective, the present study applies the UTAUT framework to analyze the structural relations among the core variables of GenAI acceptance in education and to determine the differential associations attributable to key teacher characteristics.

Method

Participants

This study targeted K-12 teachers to examine factors associated with their behavioral intention and actual use of GenAI in education, as well as the moderating role of demographic and experiential variables. An online survey was administered to K-12 teachers in South Korea from November 21 to November 30, 2023. A total of 347 teachers participated in the study, and their demographic profiles are presented in Table 1.

Table 1. Demographic profile of participants (n = 347)

Category		Frequency	%
Gender	Male	139	40.1
	Female	208	59.9
Age	In their 20s	41	11.8
	In their 30s	113	32.6
	In their 40s	115	33.1
	50s and above	78	22.5
Professional development experience with GenAI	Yes	189	54.5
	No	158	45.5
Daily use experience with GenAI	Yes	231	66.6
	No	116	33.4

Research Instruments

The measurement instruments were developed based on the UTAUT proposed by Venkatesh et al. (2012) and refined in reference to prior studies conducted in similar educational contexts, particularly those by Kim and Lee (2021). In this survey, GenAI was presented in a restricted sense, referring specifically to its use by teachers for instructional purposes. Specifically, examples were provided such as lesson planning and instructional design, creating and revising teaching and learning materials, and school administrative tasks. All items were adapted to reflect the realities of K-12 classrooms and the practical use of GenAI in education. Each variable was measured using a five-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The constructs consisted of two to five items each. To ensure clarity and content validity, three experts in educational technology and teacher education reviewed the wording and conceptual alignment of each item. In addition, a pilot test was conducted with a small group of teachers to verify item comprehensibility and linguistic appropriateness within the school context.

Performance expectancy was measured as the degree to which teachers believed that using GenAI in their teaching would enhance instructional effectiveness and work efficiency. Effort expectancy assessed the perceived ease and convenience of using GenAI tools in class or administrative tasks. Social influence reflected the perceived expectations and pressures from colleagues, school administrators, and educational authorities to integrate GenAI into teaching. Facilitating conditions encompassed environmental and organizational supports, such as the availability of technical and institutional infrastructure, administrative assistance, and opportunities for teachers' professional development. Behavioral intention represented teachers' willingness and motivation to adopt GenAI in their future teaching practices. In contrast, actual use measured the frequency and extent to which teachers had already incorporated GenAI into their instructional or professional activities.

Reliability analysis indicated satisfactory internal consistency across all constructs, with Cronbach's α coefficients of .933 for performance expectancy, .893 for effort expectancy, .930 for social influence, .807 for facilitating conditions, .944 for behavioral intention, and .794 for actual use. These results demonstrate that the measurement instruments provided reliable indicators of K-12 teachers' acceptance of GenAI in education. Nevertheless, because Cronbach's α primarily assesses internal consistency, further validation was deemed necessary. Accordingly, CFA was conducted to establish construct validity by examining standardized factor loadings, CR, and AVE. Convergent and discriminant validity were subsequently evaluated to ensure the robustness of the measurement model before proceeding to SEM.

Research Model

This study developed a structural model to examine the factors associated with K-12 teachers' acceptance of GenAI in education based on the UTAUT framework. The model aimed to verify how teachers' perceptions of performance expectancy, effort expectancy, social influence, and facilitating conditions are related to their behavioral intention to use GenAI and to determine whether gender, age, professional development experience, and daily use experience moderate these relations. Furthermore, the study examined the extent to which behavioral intention predicts actual use of GenAI in educational contexts. As illustrated in Fig. 1, the proposed model extends the original UTAUT structure by integrating demographic and experiential moderators relevant to K-12 education. This extended framework enables a more comprehensive understanding of how personal and contextual factors jointly shape teachers' adoption of emerging AI technologies. By analyzing the structural relations among these variables, the study sought to reveal both direct and indirect pathways associated with teachers' acceptance and utilization of GenAI in instructional and administrative practices.

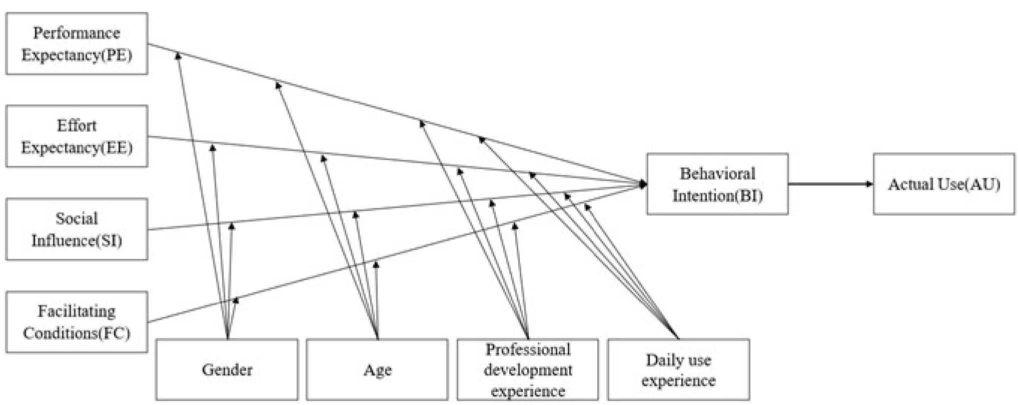

Fig. 1. Hypothetical research model

Data Analysis Procedures

The data analysis in this study followed a multi-step process designed to ensure statistical robustness and validity. First, descriptive statistics, including means, standard deviations, skewness, and kurtosis, were computed to examine the distributional characteristics of each variable. Following the criteria suggested by West et al. (1995), normality was considered acceptable when the skewness was less than 2 and the kurtosis was less than 7. To assess multicollinearity, the variance inflation factor (VIF) was calculated, with values near 1 indicating the absence of collinearity problems. Second, CFA was performed to verify the measurement validity of the latent constructs. Convergent validity was assessed through standardized factor loadings, CR, and AVE. In contrast, discriminant validity was evaluated by comparing the square roots of AVE values with the inter-construct correlations, following the criterion established by Fornell and Larcker (1981). Third, SEM was conducted to examine the hypothesized associations among performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and actual use. Model fit was evaluated using the comparative fit index (CFI), Tucker–Lewis index (TLI), and root mean square error of approximation (RMSEA), with acceptable thresholds of CFI and TLI ≥ .90 and RMSEA ≤ .08, as recommended by Hu and Bentler (1999). Fourth, associations were decomposed to analyze direct, indirect, and total associations among the latent variables. The significance of indirect associations was tested using the bootstrapping method with 2,000 resamples and 95% confidence intervals. An indirect association was considered statistically significant when the confidence interval did not include zero (Preacher & Hayes, 2008). Finally, multi-group SEM analyses were conducted to examine the differential associations attributable to teachers' personal characteristics (gender and age) and experiential characteristics (professional development and daily use) on the structural relations. The analysis followed a sequential invariance testing procedure, which compared the unconstrained and constrained models to assess the equivalence of measurement and structural paths across groups. All analyses were performed using AMOS 26.0 and SPSS 29.0, with a significance level of .05 for all statistical tests.

Results

Descriptive Statistics and Correlation Analysis

Descriptive statistics were computed to examine the mean, standard deviation, skewness, and kurtosis of the major variables included in the structural equation model, as presented in Table 2. According to the criteria suggested by West et al. (1995), all variables met the assumption of normality, with skewness values below 2 and kurtosis values below 7, indicating that the data distribution was appropriate for subsequent structural modeling.

Table 2. Descriptive statistics (n = 347)

Category	Item	*M*	*SD*	Skewness	Kurtosis
PE	PE1	4.06	0.868	-0.897	0.866
	PE2	3.88	0.964	-0.683	0.161
	PE3	3.80	0.963	-0.518	-0.140
	PE4	3.90	0.973	-0.725	0.173
	PE5	4.13	0.939	-1.188	1.418
EE	EE1	3.47	1.046	-0.217	-0.562
	EE2	2.57	1.191	0.524	-0.533
	EE3	2.74	1.168	0.336	-0.613
	EE4	2.90	1.102	0.129	-0.655
	EE5	2.91	1.174	0.062	-0.835
SI	SI1	3.12	1.190	-0.116	-0.820
	SI2	3.07	1.156	-0.102	-0.777
	SI3	3.14	1.166	-0.167	-0.765
FC	FC1	2.63	1.196	0.270	-0.868
	FC2	2.97	1.216	-0.148	-1.016
	FC3	3.50	0.998	-0.627	0.161
	FC4	2.80	1.267	0.190	-1.037
BI	BI1	3.67	1.045	-0.721	0.088
	BI2	3.54	1.123	-0.560	-0.275
	BI3	3.40	1.101	-0.353	-0.523
	BI4	3.88	0.997	-1.018	0.913
	BI5	3.76	0.972	-0.700	0.321
AU	AU1	1.95	1.030	0.918	0.145
	AU2	1.62	0.997	1.824	2.949

Following this, correlation analyses were conducted to assess the interrelations among the latent variables, as shown in Table 3. All correlations were statistically significant at the $p < .01$ level, demonstrating meaningful associations among the constructs. To further assess the potential for multicollinearity, VIF values were calculated. The results showed that all VIF values were slightly above 1, indicating no multicollinearity problems.

Table 3. Correlation matrix among latent variables (n = 347)

Variable	PE	EE	SI	FC	BI	AU
PE	1					
EE	.443**	1				
SI	.554**	.469**	1			
FC	.473**	.639**	.623**	1		
BI	.798**	.502**	.586**	.583**	1	
AU	.379**	.445**	.423**	.575**	.450**	1

*$p < .05$, **$p < .01$, ***$p < .001$

Measurement Model Testing

The results of the measurement model testing are presented in Table 4. Although the chi-square statistic was significant ($\chi^2 = 736.562$, $p < .001$), this value is known to be sensitive to sample size and, therefore, tends to overestimate model misfit. Consequently, alternative fit indices were examined to evaluate the adequacy of the measurement model. The results showed that the model demonstrated an acceptable level of fit (TLI = .917, CFI = .929, RMSEA = .078), meeting the commonly accepted thresholds (Hu & Bentler, 1999). All standardized factor loadings were above .645 and statistically significant ($p < .001$), indicating that each observed variable appropriately represented its corresponding latent construct.

Table 4. Goodness-of-fit and standardized factor loadings for the measurement model

Variable	Item	Estimate		S.E.	C.R.
		B	*β*		
PE	PE5	1	0.76		
	PE4	1.162	0.852	0.068	17.111***
	PE3	1.23	0.912	0.066	18.583***
	PE2	1.231	0.911	0.066	18.569***
	PE1	1.05	0.863	0.06	17.383***
EE	EE5	1	0.738		
	EE4	1.107	0.871	0.068	16.282***
	EE3	1.187	0.881	0.072	16.469***
	EE2	1.125	0.819	0.074	15.262***
	EE1	0.793	0.657	0.066	12.064***
SI	SI3	1	0.902		
	SI2	1.01	0.918	0.038	26.303***
	SI1	1.008	0.891	0.041	24.703***
FC	FC4	1	0.645		
	FC3	0.766	0.627	0.076	10.073***
	FC2	1.207	0.812	0.098	12.328***
	FC1	1.174	0.803	0.096	12.232***
BI	BI1	1	0.872		
	BI2	1.111	0.902	0.046	24.333***
	BI3	1.091	0.904	0.045	24.453***
	BI4	0.932	0.853	0.043	21.676***
	BI5	0.923	0.865	0.041	22.309***
AU	AU1	1	0.779		
	AU2	1.051	0.846	0.084	12.458***

*$p < .05$, **$p < .01$, ***$p < .001$

As shown in Table 5, the composite reliability (CR) values ranged from .75 to .93, all exceeding the threshold of .70, thereby confirming internal consistency. The average variance extracted (AVE) values were generally above .50, indicating convergent validity. Although the AVE value for Facilitating Conditions (.49) was slightly below the recommended criterion, its CR value (.78) satisfied the acceptable standard, suggesting that convergent validity was generally established (Hair et al., 2019). Furthermore, discriminant validity was confirmed, as the square root of each AVE (diagonal elements) exceeded the corresponding inter-construct correlations.

Table 5. Results of discriminant validity analysis (n = 347)

Variable	PE	EE	SI	FC	BI	AU	AVE	CR
PE	0.86						0.74	0.91
EE	0.46	0.81					0.66	0.85
SI	0.58	0.52	0.87				0.76	0.9
FC	0.48	0.47	0.49	0.7			0.49	0.78
BI	0.69	0.6	0.62	0.65	0.9		0.81	0.93
AU	0.42	0.38	0.41	0.44	0.59	0.73	0.54	0.75

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Structural Model Testing

The results of the structural model testing are presented in Table 6 and Fig 2. The model demonstrated an acceptable level of overall fit (χ^2 = 780.562, p < .001, TLI = .911, CFI = .918, RMSEA = .079), which meets the recommended thresholds suggested by Hu and Bentler (1999). The path coefficient analysis revealed that Performance Expectancy (β = .758, p < .001), Social Influence (β = .130, p < .001), and Facilitating Conditions (β = .263, p < .001) were significantly and positively associated with Behavioral Intention to use GenAI in education. Among these, Performance Expectancy showed the strongest association, indicating that teachers' expectations of educational and professional benefits from using GenAI were the most strongly related to their intention to adopt it. In contrast, Effort Expectancy (β = .083, p = .072) was not statistically significant, suggesting that teachers' perceptions of ease were not directly associated with their behavioral intention. Furthermore, Behavioral Intention (β = .487, p < .001) had a significant positive association with Actual Use, demonstrating that teachers' perceived intention plays a crucial mediating role in translating cognitive beliefs into actual implementation behaviors.

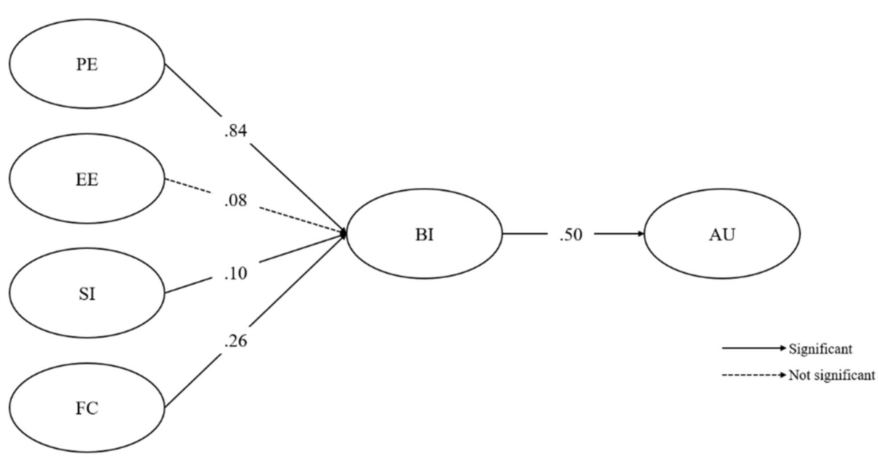

Fig. 2. Standardized path coefficients of the structural model

Table 6. Path coefficients and significance of the structural model (n = 347)

Path		Estimate		S.E.	C.R.
		B	*β*		
BI	←PE	0.835	0.758	0.063	13.252***
	←EE	0.076	0.083	0.035	2.186
	←SI	0.098	0.130	0.028	3.432***
	←FC	0.26	0.263	0.044	5.908***
AU	←BI	0.502	0.487	0.068	7.356***

*$p < .05$, **$p < .01$, ***$p < .001$

Direct and Indirect Associations

The results of the decomposition of associations in the final structural model are summarized in Table 7. Performance Expectancy, Social Influence, and Facilitating Conditions showed significant positive associations with Behavioral Intention, with Performance Expectancy ($\beta = .76, p < .001$) emerging as the most strongly associated factor. In contrast, the association of Effort Expectancy with Behavioral Intention was weak and not statistically significant. Behavioral Intention showed a significant positive direct association with Actual Use ($\beta = .49, p < .001$), representing the strongest direct path in the final model. This finding indicates that teachers' intention to integrate GenAI into their instructional practices serves as a crucial bridge linking cognitive perceptions and actual implementation behavior. The analysis of indirect associations further revealed that Performance Expectancy ($\beta = .37, p < .001$) and Facilitating Conditions ($\beta = .13, p < .01$) were associated with Actual Use indirectly through Behavioral Intention. Social Influence also had a significant but relatively weaker association with Actual Use ($\beta = .06, p < .05$). Conversely, the indirect association with Effort Expectancy was not statistically significant. The results of the bootstrapping procedure (2,000 resamples, 95% confidence interval) confirmed the significance of the indirect associations of Performance Expectancy (.22~.51) and Facilitating Conditions (.06~.21), as zero was not included in the confidence intervals. The indirect association with Social Influence (.01~.12) was also significant but modest in magnitude. These findings suggest that Performance Expectancy and Facilitating Conditions are key determinants of Actual Use, operating primarily through Behavioral Intention, which serves as the most powerful explanatory factor for teachers' adoption of GenAI in education. In contrast, Effort Expectancy demonstrated limited explanatory power within the overall model.

Table 7. Decomposition of direct and indirect effects in the final model (n = 347)

Path		Direct Effect	Indirect Effect	Total Effect	95%CI(I ndirect)	*p*
BI	←PE	0.76	-	0.76	-	.000
	←EE	0.08	-	0.08	-	.072
	←SI	0.13	-	0.13	-	.018
	←FC	0.26	-	0.26	-	.004
AU	←PE	-	0.37	0.37	.22 ~ .51	.000
	←EE	-	0.04	0.04	.00 ~ .10	.119
	←SI	-	0.06	0.06	.01 ~ .12	.041
	←FC	-	0.13	0.13	.06 ~ .21	.002
	←BI	0.49	-	0.49	-	.000

Moderation Analysis

First, the results of the multi-group analysis by gender are presented in Table 8. For both male and female teachers, Performance Expectancy (male: β = .76; female: β = .74), Social Influence (male: β = .13; female: β = .14), and Facilitating Conditions (male: β = .26; female: β = .27) showed significant positive associations with Behavioral Intention. In contrast, the association with Effort Expectancy was not significant in either group (male: β = .08; female: β = .04). The path difference test revealed no statistically significant differences between the groups. In summary, the research model was found to be equally applicable across genders, with Performance Expectancy emerging as the factor most strongly associated with Behavioral Intention in both groups, complemented by Facilitating Conditions and Social Influence as supporting factors.

Table 8. Multi-group path analysis by gender (n = 347)

Path		Male			Female			Path Difference
		B	*B*	S.E.	*B*	β	S.E.	
BI	←PE	0.84	0.76***	0.06	0.81	0.74***	0.07	1.12
	←EE	0.08	0.08	0.04	0.04	0.04	0.04	0.97
	←SI	0.1	0.13***	0.03	0.11	0.14***	0.03	1.08
	←FC	0.13	0.26***	0.04	0.14	0.27***	0.05	1.21

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Second, the results of the multi-group analysis by age are shown in Table 9. Among teachers aged in their 20s and 30s, Performance Expectancy (β = .81), Social Influence (β = .16), and Facilitating Conditions (β = .23) were significantly associated with Behavioral Intention, whereas the association with Effort Expectancy (β = .01) was not significant. For teachers aged 40 and above, Performance Expectancy (β = .72), Effort Expectancy (β = .14), Social Influence (β = .14), and Facilitating Conditions (β = .27) all showed significant associations with Behavioral Intention. The path difference test indicated a statistically significant difference only in the Effort Expectancy → Behavioral Intention path. These results suggest that, while the model structure was consistent across age groups, ease of use (Effort Expectancy) played an additional role in shaping the behavioral intention of older teachers toward GenAI integration.

Table 9. Multi-group path analysis by age (n = 347)

Path		Age 20-39			Age 40 and above			Path Difference
		B	*B*	S.E.	*B*	β	S.E.	
BI	←PE	0.94	0.81***	0.1	0.75	0.72***	0.08	1.27
	←EE	0.01	0.01	0.05	0.14	0.14**	0.04	3.11*
	←SI	0.25	0.16**	0.06	0.24	0.14**	0.06	0.52
	←FC	0.23	0.23**	0.06	0.27	0.27**	0.05	0.08

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Third, the results of the multi-group analysis by Professional Development Experience are shown in Table 10. For teachers without professional development experience, Performance Expectancy (β = .80) and Effort Expectancy (β = .21) were significantly associated with Behavioral Intention, while Social Influence (β = .08) and Facilitating Conditions (β = .10) were not significant. In contrast, for teachers with professional development experience, Performance

Expectancy (β = .67), Social Influence (β = .16), and Facilitating Conditions (β = .45) showed significant associations, while Effort Expectancy (β = -.04) did not. The path difference test revealed statistically significant differences in the Effort Expectancy, Social Influence, and Facilitating Conditions paths. Overall, the model performed differently depending on whether professional development experience was present or absent. Teachers without such experience formed their Behavioral Intention primarily based on ease of use (Effort Expectancy). In contrast, those with professional development experience were more influenced by social and institutional support (Social Influence and Facilitating Conditions).

Table 10. Multi-group path analysis by professional development experience (n = 347)

Path		No Experience			With Experience			Path Difference
		B	*B*	S.E.	*B*	β	S.E.	
BI	←PE	0.91	0.80***	0.08	0.85	0.67***	0.1	2.14
	←EE	0.21	0.21***	0.06	-0.03	-0.04	0.04	4.37*
	←SI	0.07	0.08	0.04	0.12	0.16**	0.04	3.02*
	←FC	0.11	0.1	0.06	0.43	0.45***	0.07	6.41**

*$p < .05$, **$p < .01$, ***$p < .001$

Finally, the results of the multi-group analysis by Daily Use Experience are presented in Table 11. For teachers without daily use experience, Performance Expectancy (β = .77) and Effort Expectancy (β = .25) were significantly associated with Behavioral Intention, while associations with Social Influence (β = .07) and Facilitating Conditions (β = .07) were not significant. Conversely, for teachers with daily use experience, Performance Expectancy (β = .75), Social Influence (β = .15), and Facilitating Conditions (β = .31) showed significant positive associations, whereas Effort Expectancy (β = .02) did not. Path difference testing indicated significant differences across the Effort Expectancy, Social Influence, and Facilitating Conditions paths. In summary, teachers without daily use experience primarily formed their Behavioral Intention based on technical ease of use (Effort Expectancy). In contrast, those with daily use experience relied more on social influence and facilitating conditions when forming their intention to adopt GenAI in education.

Table 11. Multi-group path analysis by daily use experience (n = 347)

Path		No Experience			With Experience			Path Difference
		B	*B*	S.E.	*B*	β	S.E.	
BI	←PE	0.88	0.77***	0.09	0.94	0.75***	0.09	1.84
	←EE	0.26	0.25***	0.07	0.02	0.02	0.04	4.92*
	←SI	0.06	0.07	0.06	0.1	0.15**	0.03	3.15*
	←FC	0.08	0.07	0.07	0.27	0.31***	0.05	5.62**

*$p < .05$, **$p < .01$, ***$p < .001$

Discussion and Implications

Discussion

This study analyzed the structural relations among performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and actual use of GenAI in education among K-12 teachers, based on the

UTAUT. In addition, it empirically examined the differential associations across groups for gender, age, professional development experience, and daily use experience. The findings revealed that the factors associated with technology acceptance varied depending on teachers' characteristics and experience levels, illustrating a differentiated pattern in the emerging educational context of GenAI. The implications of these results are discussed below in comparison with prior studies.

First, performance expectancy showed the strongest association with teachers' behavioral intention to use GenAI in education. This finding indicates that teachers' expectations of enhanced instructional outcomes and professional efficiency are more decisive than perceptions of ease of use in determining their intention to integrate GenAI into classroom practice. The result aligns with prior studies, which emphasize that perceived usefulness significantly affects technology adoption intentions (Bower et al., 2024; Davis, 1989; Dindar et al., 2021; Kim & Lee, 2021; Kittinger & Law, 2024; Venkatesh et al., 2003; Wozney et al., 2006). In other words, K-12 teachers are more likely to adopt GenAI when they believe it will lead to tangible improvements in instructional efficiency, student achievement, and work productivity.

Second, effort expectancy was not significantly associated with behavioral intention in the overall sample; however, it showed differential associations depending on age, professional development experience, and daily use experience. These findings suggest that teachers prioritize educational outcomes over ease of use when integrating GenAI into classroom instruction. At the same time, the user-friendly nature of GenAI-featuring natural language interaction and automated content generation-may have diminished the impact of perceived ease of use. This finding is consistent with prior studies, which report that effort expectancy does not significantly influence adoption intentions (Dindar et al., 2021; Kittinger & Law, 2024; Pynoo et al., 2011). However, this does not necessarily imply that the technical difficulties of operating the technology have disappeared; instead, it suggests that the primary barriers teachers actually face may have shifted toward educational implementation within instructional contexts. In other words, even if using the tool itself is relatively easy, ensuring alignment among instructional goals, learning activities, and assessment, designing prompts appropriate to learners' levels, and pedagogically designing and integrating the generated outputs requires additional expertise and effort. Meanwhile, as proposed by Venkatesh et al. (2003), age and experience serve as moderating variables that alter the strength of effort expectancy's effects. In this study, effort expectancy had a stronger association among teachers aged 40 and older, those with limited professional development experience, and those without daily use experience. These findings reaffirm previous findings that older or less experienced teachers perceive ease of use as a critical facilitator or barrier to technology integration (Dindar et al., 2021; O'Bannon & Thomas, 2014). Meanwhile, this finding should be interpreted not merely as a function of lower digital literacy or an age effect, but rather through the lens of expert inertia. In other words, sensitivity to effort expectancy may reflect not only the difficulty of operating the tool itself but also the burden associated with integrating generative AI into long-established instructional strategies, classroom routines, and assessment practices.

Third, social influence and facilitating conditions were indirectly associated with actual use through behavioral intention. Moreover, professional development and daily use experience showed differences in these paths, with experienced teachers showing strong associations with social and institutional support. These findings highlight the importance of positive support from school administrators and colleagues, as well as sufficient financial, technical, and infrastructural resources-such as stable networks and technical assistance-in shaping teachers' intentions and actual adoption behaviors. Prior studies similarly emphasized that technology adoption is strengthened when individual perceptions are supported by institutional and environmental factors (Kim & Lee, 2021; Kittinger & Law, 2024; Tosuntaş et al., 2015). The present study corroborates this argument in the context of GenAI, suggesting that as teachers gain experience, they increasingly rely on organizational infrastructure and peer support to meaningfully integrate technology for pedagogical purposes rather than simply using it as a tool. Moreover, the finding that the effects of social influence and facilitating conditions were relatively more substantial in the group with professional development experience may reflect a transition in teachers' use of generative AI from individual exploration to system-level integration. That is, once PD provides teachers with a foundational level of experience and understanding, acceptance may be shaped more strongly not only by individual considerations but also by organizational norms and expectations within schools, as well as by support conditions that enable implementation.

Finally, this study empirically confirmed the structural relation between behavioral intention and actual use. Behavioral intention had a significant positive association with actual use, and performance expectancy, social influence, and facilitating conditions were indirectly associated with actual use through behavioral intention. These findings indicate that teachers with higher expectations for GenAI's benefits, stronger perceptions of social endorsement, and greater institutional or technical support are more likely to integrate GenAI into their teaching practices. This result is consistent with prior research demonstrating that behavioral intention serves as a crucial link between perception and actual behavior (Kim & Lee, 2021; Muhamed & Kamsin, 2025; Or, 2023). Accordingly, this study provides empirical evidence that teachers' behavioral intention is the key mediating variable predicting their actual educational use of GenAI.

Implications

By applying the UTAUT model to analyze teachers' acceptance of GenAI in education, this study expands our understanding of technology adoption mechanisms in rapidly evolving educational contexts. The findings hold several theoretical and practical implications.

First, the results indicate that teachers' behavioral intention to use GenAI is most strongly associated with their expectations of instructional and professional performance outcomes. This finding suggests that teachers' acceptance of GenAI depends not merely on learning how to use the technology, but on experiencing tangible educational and administrative benefits such as improved teaching quality, enhanced efficiency, and increased student engagement. Therefore, educational authorities and schools should move beyond training programs focused on basic functionality and instead develop policy supports and professional learning opportunities that allow teachers to experience the educational value of GenAI firsthand. For instance, task-based action learning programs, subject-specific application workshops, and hands-on training in lesson planning and assessment automation could help teachers perceive GenAI's effectiveness within authentic teaching contexts.

Second, although effort expectancy did not show a significant association with behavioral intention in the overall model, it emerged as a key determinant for teachers aged 40 and above, as well as those with limited professional development or daily use experience. This finding implies that ease of use remains a critical entry barrier for certain teacher groups, particularly those less familiar with emerging technologies. To address this, customized training modules should be designed according to teachers' age and experience levels. Practical resources-such as user guides for educational and administrative GenAI tools, sample prompts, and access to automated teaching and learning agents-can enhance perceived simplicity and support teachers' confidence in using the technology effectively.

Third, teachers' adoption of GenAI should be understood as an interaction between individual, organizational, and environmental factors, rather than as a matter of personal attitude alone. The findings revealed that social influence and facilitating conditions showed significant indirect associations with actual use through behavioral intention. In addition, the finding that actual use was substantially lower than the mean level of behavioral intention suggests that teachers may hold a firm intention to use generative AI. Yet, a clear intention-behavior gap exists in translating that intention into actual instructional or work-related practice. This gap can be interpreted as a typical pattern observed during the early stage of introducing generative AI into educational settings, as implementation often entails additional execution burdens such as ensuring alignment among instructional goals, learning activities, and assessment, evaluating the pedagogical validity and quality of generated outputs, and designing implementation procedures and role allocations. This finding emphasizes the importance of supportive school ecosystems-including leadership endorsement, peer collaboration, and access to stable digital infrastructure and technical support. Educational authorities and school leaders should strengthen digital infrastructure policies, establish teacher learning communities, and foster AI literacy among administrators to create a safe and enabling environment for GenAI exploration. Furthermore, as both the present and prior studies indicate, more experienced teachers tend to rely increasingly on social and organizational support structures, underscoring the need for sustainable and pedagogically meaningful integration of GenAI to require institutional backing and collaborative professional cultures, moving beyond individual experimentation to systemic adoption.

Limitations

Although this study provided insight into the structural relations underlying K-12 teachers' acceptance of GenAI in education, several limitations should be acknowledged.

First, the study adopted a cross-sectional design, which limits the ability to explain temporal changes and causal relations among the variables. Future research should employ longitudinal designs to track how teachers' initial attitudes toward GenAI evolve into actual and sustained use, and to examine the long-term effects of educational or policy interventions.

Second, the data relied on self-reported survey responses, which may not fully capture the complexity of teachers' behaviors in authentic classroom contexts. To gain a more comprehensive understanding, future studies should integrate objective data sources, such as log files, classroom observations, and student outputs, to construct multidimensional indicators of GenAI use.

Third, the present analysis focused on the core variables of the UTAUT model and a limited set of demographic moderators. Future research could extend the model by incorporating contextual and psychological variables such as teachers' pedagogical beliefs, ethical considerations, technology anxiety, and digital divide issues, thereby enhancing the explanatory power of the model in GenAI-based educational environments.

Finally, this study collected data via an online survey, which may have introduced self-selection bias, as teachers who already held relatively positive attitudes toward, or a more substantial interest in, generative AI and digital technologies may have been more likely to participate. Indeed, the sample exhibited an overall tendency toward favorable responses-for example, the mean score for Performance Expectancy among the UTAUT constructs exceeded 4.0, making it difficult to rule out the possibility that levels of key perceptual variables and Behavioral Intention were higher than those of the broader teacher population. Accordingly, this sampling characteristic should be taken into account when interpreting the findings, particularly with respect to Behavioral Intention and Actual Use. Future research should employ diverse sampling strategies, such as stratified sampling, to improve sample representativeness.

Conflicts of Interest

The author(s) declared no conflicts of interest.

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Appendix. Survey Items

Performance Expectancy

PE1. I think using GenAI can provide diverse and useful information needed for instruction.

PE2. I think using GenAI can improve the quality of my instruction.

PE3. I think using GenAI can improve instructional outcomes.

PE4. I think using GenAI can improve my instructional methods.

PE5. I think using GenAI can be helpful and convenient for my teaching, work, or daily life.

Effort Expectancy

EE1. I find GenAI-integrated instruction easy to understand.

EE2. I can implement GenAI-integrated instruction easily without much effort.

EE3. Becoming skillful at implementing GenAI-integrated instruction would be easy.

EE4. Learning how to implement GenAI-integrated instruction in class is easy.

EE5. I can implement GenAI-integrated instruction in class without help from others.

Social Influence

SI1. People who are important to me think that I should implement GenAI-integrated instruction (these people refer to administrators or fellow teachers).

SI2. People who can influence my behavior think that I should implement GenAI-integrated instruction.

SI3. People whose opinions I value think that I should implement GenAI-integrated instruction.

Facilitating Conditions

FC1. I have the resources necessary to implement GenAI-integrated instruction.

FC2. I have the knowledge necessary to implement GenAI-integrated instruction.

FC3. GenAI-integrated instruction integrates well with other instructional content.

FC4. When I have difficulties implementing GenAI-integrated instruction, there is someone who can help me.

Behavioral Intention

BI1. I intend to implement GenAI-integrated instruction in my classes.

BI2. I intend to recommend GenAI-integrated instruction to others.

BI3. I will continue to implement GenAI-integrated instruction in my classes.

BI4. I expect GenAI-integrated instruction to make classes more interesting.

BI5. I expect GenAI-integrated instruction to bring positive changes to my classes.

Actual Use

AU1. How often do you use GenAI in your classes?

AU2. On average, how many times per month do you implement GenAI-integrated instruction?