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Social and Pedagogical Drivers of ChatGPT Acceptance: An Extended TAM Model in Teacher Education

Halit Karalar *
Department of Educational Technology and Instructional Technology, Muğla Sıtkı Koçman University, Muğla, Türkiye
ORCID: 0000-0001-9344-9672

Sedat Altıntaş
Department of Curriculum and Instruction, Sinop University, Sinop, Türkiye
ORCID: 0000-0003-4637-561X

Bilge Aslan Altan
Department of Curriculum and Instruction, Muğla Sıtkı Koçman University, Muğla, Türkiye
ORCID: 0000-0002-3309-933X

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Generative artificial intelligence tools, particularly applications such as ChatGPT, hold significant potential to reshape the landscape of teacher education by offering opportunities for personalized feedback and adaptive learning. These tools also play important roles in teachers' pedagogical decisions while designing their teachings in present learning environments. However, the underlying mechanisms driving pre-service teachers' adoption of such particular tools remain under-explored. This study addresses this gap by validating an extended technology acceptance model incorporating constructivist teaching beliefs, subjective norms, facilitating conditions, ChatGPT self-efficacy, and perceived enjoyment. Data collected from 488 senior pre-service teachers in Türkiye were analyzed using structural equation modeling. Results show that ChatGPT self-efficacy and perceived enjoyment significantly predict perceived ease of use, whereas facilitating conditions do not exert a significant influence. Perceived usefulness is significantly associated with perceived ease of use, subjective norms, and pedagogical beliefs. Behavioral intention is significantly associated with perceived usefulness, subjective norms, and ChatGPT self-efficacy, with the framework explaining 54% of the variance. Given the cross-sectional nature of the data, these results offer tentative implications for teacher education. Practically, the findings highlight the potential value of scaffolded micro-teaching and institutional verification procedures for supporting responsible and equitable generative AI use in teacher education. Further recommendations are discussed in the light of teacher education procedures and policies.

* Correspondency: halit@mu.edu.tr

Introduction

Generative artificial intelligence (GenAI) has transformed multiple domains by enabling the creation of novel content through advanced architectures such as Generative Adversarial Networks (GAN) and transformer-based models (e.g., GPT family) (Sun et al., 2025). Among these innovations, ChatGPT, launched by OpenAI in 2022, experienced exceptionally rapid adoption, reaching one million users within five days and 100 million within two months, making it the fastest-growing consumer application in history (OpenAI, 2023; Milmo, 2023). This rapid adoption has sparked intense debate in education, particularly in teacher preparation, where ChatGPT's potential for personalized feedback and adaptive learning pathways is widely acknowledged (Crompton & Burke, 2024; UNESCO, 2024).

ChatGPT interacts with learners in a conversational style, instantly generating diverse content and providing real-time, individualized feedback (Zhong et al., 2025). Research highlights its capacity associated with improved learning performance learning performance, fostered positive perceptions, and stimulated higher-order thinking (Wang & Fan, 2025; Deng et al., 2025). It has been also reported to increase behavioral, cognitive, and emotional engagement (Heung & Chiu, 2025), strengthen self-efficacy, and reduce cognitive load. For pre-service teachers, who remain learners themselves, ChatGPT offers additional benefits, including improved lesson planning skills (Cai et al., 2025), opportunities for creative content development (Korucu-Kış, 2024), and personalized professional growth (Şimşek, 2025).

However, these advantages are accompanied by notable challenges. Studies report risks such as inaccurate responses, academic plagiarism, and overreliance on technology (Ali et al., 2024), as well as reduced teacher-student interaction and diminished critical thinking (Dempere et al., 2023; Haque & Li, 2025; Zhang & Tur, 2024). Ethical concerns—including academic integrity, privacy, bias, and hallucinations—further complicate integration (Mustafa et al., 2024; Sharples, 2023; Yadav & Sharma, 2024). Fully leveraging ChatGPT's potential therefore requires preparing pre-service teachers to adopt and use it responsibly in future classrooms (UNESCO, 2024).

Successful GenAI integration depends partly on pre-service teachers' acceptance and readiness. Initiatives such as the FATİH Project and digital developments during the COVID-19 pandemic have contributed to improvements in digital infrastructure in Türkiye (Aypay et al., 2012; Gökçearslan et al., 2022). Consequently, the focus has shifted from simple use to the psychological and pedagogical drivers of adoption. Prior research indicates that behavioral intention toward GenAI is shaped by perceived usefulness, ease of use, and subjective norms (Sun et al., 2025; Zhang et al., 2023). However, while traditional models such as TAM focus on functional perceptions, GenAI adoption is increasingly recognized as a normative process. Yet, little is known about how internal pedagogical frameworks, specifically constructivist teaching beliefs, interact with these determinants. While constructivism emphasizes inquiry and learner-centered scaffolds, ChatGPT's conversational nature offers an authentic way for such practices. Furthermore, existing studies have focused primarily on first-order barriers (e.g., facilitating conditions) and second-order barriers (e.g., self-efficacy) without fully integrating social influence mechanisms and belief systems into a cohesive framework (Huang & Teo, 2021; Ramnarain et al., 2025). Addressing this gap, the present study examines how pedagogical beliefs, subjective norms, and individual efficacy are associated with GenAI acceptance in teacher education.

Theoretical framework

Technology integration in education is shaped by multiple individual, contextual, and institutional factors influencing its success (Ertmer, 1999; Ertmer & Ottenbreit-Leftwich, 2010; Hew & Brush, 2006). These factors are often examined through the lens of technology acceptance, which refers to the extent to which individuals and organizations adopt and effectively use technological innovations (Scherer et al., 2019). In educational contexts, technology acceptance has been widely studied to understand how digital tools can support student-centered learning, enhance instructional practices, and improve performance (Mejía-Mancilla & Mejía-Trejo, 2024; Teo et al., 2009).

Although originally developed for information systems, several theoretical models have been applied to explain technology adoption in education, including the Theory of Reasoned Action (Ajzen & Fishbein, 1980), Diffusion of Innovation (Rogers, 1983), Social Cognitive Theory (Bandura, 1986), the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Planned Behavior (Ajzen, 1991), and the Motivation Model (Davis et al., 1992). Among these, TAM has become one of the most influential frameworks for predicting technology use. TAM posits that perceived usefulness and perceived ease of use are key determinants of behavioral intention to use technology (Davis, 1989). Attitude toward use was included as a mediator in the original TAM but was omitted from later versions of the model (Figure 1).

TAM is one of the most widely applied models for explaining technology acceptance among both in-service and pre-service teachers (Granić & Marangunić, 2019; Scherer et al., 2019; Scherer & Teo, 2019). In studies with pre-service teachers, TAM has been extensively employed to examine the adoption of artificial intelligence (Alrishan, 2023; Sun et al., 2025; Zhang et al., 2023), mobile technologies (Sánchez-Prieto et al., 2019), Internet of Things for educational purposes (Gökçearslan et al., 2024), and computer-assisted language learning (Mei et al., 2018). These studies demonstrate the broad application of TAM in teacher education contexts. Building on this foundation, the present study extends TAM to examine factors associated with pre-service teachers' acceptance of ChatGPT in teacher education.

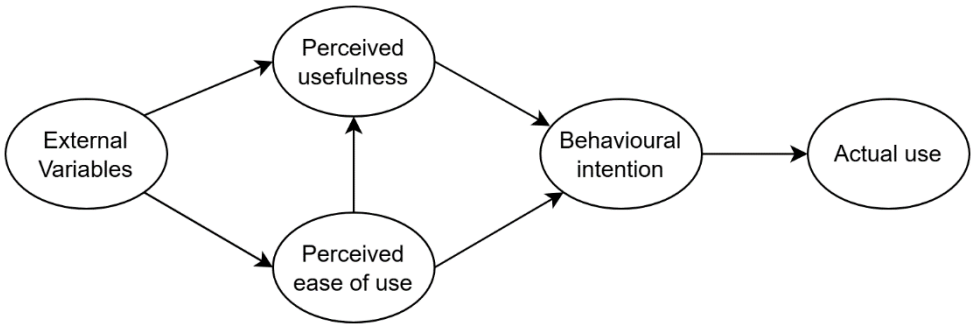


Figure 1. *Technology Acceptance Model (Davis & Venkatesh, 1996)*

Research hypotheses

Perceived usefulness (PU)

Perceived usefulness (PU), a core construct of the Technology Acceptance Model (TAM), reflects the extent to which users believe that a technology enhances their performance. In educational contexts, has been identified as an important predictor of attitudes and behavioral intentions toward technology use (Teo et al., 2009; Yang & Chen,

2022). When pre-service teachers perceive ChatGPT as beneficial for teaching and learning, they may be more likely to intend to use it. Accordingly, the first hypothesis is:

H1: Perceived usefulness is positively associated with behavioral intention to use ChatGPT.

Perceived ease of use (PEU)

Perceived ease of use (PEU) refers to the degree to which an individual believes that using a technology requires little effort. Research consistently shows that ease of use is positively associated with both perceived usefulness and behavioral intention (Cambra-Fierro et al., 2024; Lim et al., 2024; Shahzad et al., 2024). Thus, the following hypotheses are proposed:

H2: Perceived ease of use is positively associated with perceived usefulness.

H3: Perceived ease of use is positively associated with behavioral intention to use ChatGPT.

Subjective norm (SN)

Subjective norm refers to the perceived social pressure from important others to perform or not perform a particular behavior. In educational settings, peer and institutional expectations have been associated with technology adoption (Khlaisang et al., 2021; Ursavaş et al., 2019). When pre-service teachers perceive that important others support the use of ChatGPT, they may be more likely to perceive it as useful and intend to use it. (Yang & Chen, 2022; Chen et al., 2024). Therefore:

H4: Subjective norm is positively associated with perceived usefulness.

H5: Subjective norm is positively associated with behavioral intention to use ChatGPT.

Constructivist teaching beliefs (CTB)

Teaching beliefs guide instructional decisions. Constructivist beliefs emphasize active learning and knowledge construction, which may align with the interactive features of ChatGPT (Teo et al., 2008; Teo et al., 2018). Prior studies suggest that constructivist are positively associated with perceptions of technology's pedagogical value (Huang & Teo, 2021; Acosta-Enriquez et al., 2025). Thus:

H6: Constructivist teaching beliefs are positively associated with perceived usefulness.

ChatGPT self-efficacy (CSE)

ChatGPT self-efficacy refers to individuals' beliefs in their ability to use ChatGPT effectively and it has been associated with perceptions of ease of use and usefulness (Islamoglu et al., 2021; Sukirman et al., 2024). Pre-service teachers with higher ChatGPT self-efficacy are more confident in using the tool effectively. Therefore:

H7: ChatGPT self-efficacy is positively associated with perceived ease of use.

H8: ChatGPT self-efficacy is positively associated with behavioral intention to use ChatGPT.

Perceived enjoyment (PE)

Perceived enjoyment refers to the degree to which using a technology is perceived as pleasant or intrinsically rewarding, and it has been linked to both behavioral intention and actual technology use. Perceived enjoyment has also been matched with perceived usefulness and perceived ease of use (Sánchez-Prieto et al., 2019; Teo et al., 2019). When pre-service teachers perceive ChatGPT as enjoyable and pedagogically valuable, they may report stronger intentions to use it. (Cambra-Fierro et al., 2024). This construct has therefore been integrated into the extended TAM framework to capture its role in shaping acceptance. Accordingly, the following hypotheses are proposed:

H9: Perceived enjoyment is positively associated with perceived ease of use.

H10: Perceived enjoyment is positively associated with behavioral intention to use ChatGPT.

Facilitating conditions (FC)

Facilitating conditions refer to the resources, infrastructure, and support systems that enable effective technology use. These conditions have been associated with individuals' intentions and ability to use new technologies (Gökçearslan et al., 2022; Teo et al., 2019). In the context of ChatGPT, facilitating conditions include institutional support, technical resources, and training opportunities that may be associated with perceived ease of use (Aypay et al., 2012; Teo & Milutinovic, 2015). Therefore:

H11: Facilitating conditions are positively associated with perceived ease of use.

Building on these constructs, this study introduces an extended TAM framework to identify the factors shaping pre-service teachers' intention to use ChatGPT in their future teaching practices (see Figure 2).

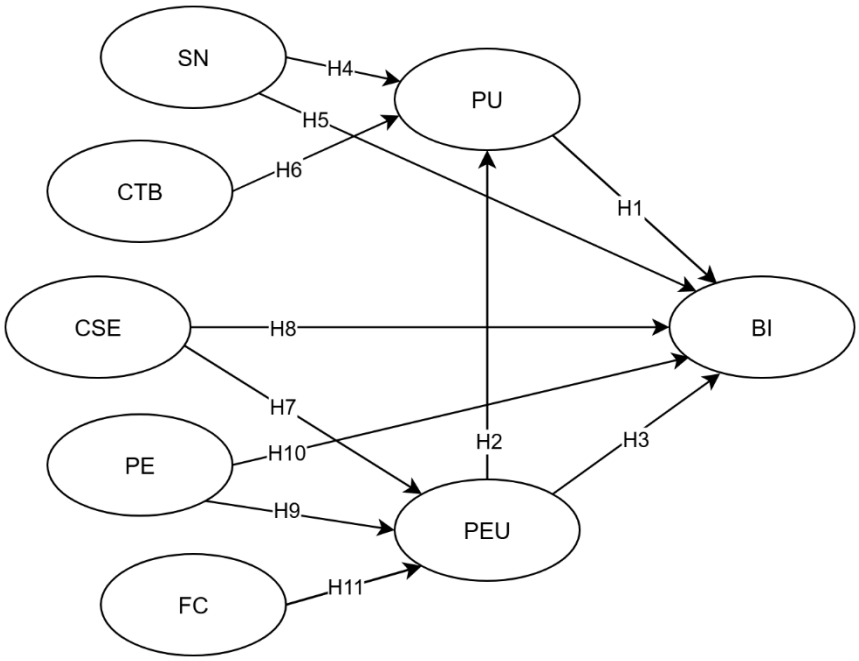


Figure 2. *Research Model*

Aims and Research Questions

Building on the extended Technology Acceptance Model (TAM), this study aims to examine the factors associated with pre-service teachers' behavioral intentions to use ChatGPT in their future classrooms. Specifically, the study addresses the following research questions:

- To what extent does the extended TAM explain pre-service teachers' behavioral intentions to use ChatGPT in their future classrooms?
- What are the direct and indirect associations between the proposed predictors and pre-service teachers' behavioral intentions to use ChatGPT?

Method

Research Design

This study employed a cross-sectional correlational research design to examine the structural relationships among factors associated with pre-service teachers' intentions to use ChatGPT. Correlational designs allow relationships among multiple variables to be examined and an outcome to be predicted from several predictors without experimental manipulation (Fraenkel et al., 2022). This design was uniquely suited to evaluate how pedagogical beliefs, social influences, and intrinsic motivators are related within the extended TAM. The cross-sectional approach facilitated data collection at a single point in time, providing a snapshot of senior pre-service teachers' adoption readiness just prior to entering the profession.

Participants

The sample consisted of 488 senior pre-service teachers selected via convenience sampling from education faculties at three public universities across different regions in Türkiye. To ensure sample eligibility, the following inclusion criteria were applied: participants had to be in their final (fourth) academic year, enrolled in a formal teacher education program, and have prior experience using ChatGPT for academic or instructional tasks. Students who had never utilized generative AI tools were excluded from the study. Among the eligible participants, 63.9% were female, and their average age was 22.31 years (SD = 1.56; see Table 1). A priori power analysis using Soper's (2021) web-based calculator indicated that a minimum sample size of 444 participants was required to achieve an effect size of 0.20, statistical power of 0.80, and a significance level of 0.05, indicating that the final sample size (N = 488) exceeded the minimum requirement.

In addition to demographic data, participants were asked to describe their primary reasons for using ChatGPT. The most frequently reported purposes were completing assigned homework and preparing lessons (f = 234), followed by acquiring information and gaining insights (f = 79). Other notable uses included conducting research (f = 77) and writing or editing tasks (f = 17). These findings suggest that pre-service teachers primarily employ ChatGPT for academic and professional purposes. In contrast, less common uses included entertainment (f = 8) and coding (f = 4), indicating that non-academic applications are relatively rare.

Table 1. *Demographic Characteristics of Pre-Service Teachers*

		N	%
Gender	Male	176	36.1
	Female	312	63.9
	Total	488	100
Program	German Language Education	35	7.2
	English Language Education	52	10.7
	Elementary Mathematics Education	38	7.8
	Science Education	54	11.1
	Primary School Education	73	15.0
	Early Childhood Education	76	15.6
	Psychological Counseling and Guidance	86	17.6
	Turkish Education	47	9.6
	Social Science Education	27	5.5
	Total	488	100

Note. N = number of respondents; % = percentage of participants.

Data Collection Procedure

Data were collected during the fall semester of the 2025-2026 academic year over a three-week period. An online survey link was distributed to potential participants via institutional communication channels and student networks. Participation was entirely voluntary, and digital informed consent was obtained from all participants before they completed the survey. Of the 520 pre-service teachers who accessed the survey, 495 completed it, yielding an initial response rate of 95.1%. Before analysis, the data were screened for missing values.; seven incomplete responses with more than 5% missing data were excluded, resulting in a final sample of 488 participants.

Data Collection Tool

The survey consisted of two sections. The first section gathered demographic information, such as gender, age, and academic program. The second section included items rated on a five-point Likert scale measuring eight constructs: subjective norm (three items, $\alpha = 0.795$), constructivist teaching beliefs (five items, $\alpha = 0.862$), ChatGPT self-efficacy (four items, $\alpha = 0.844$), perceived enjoyment (three items, $\alpha = 0.895$), facilitating conditions (three items, $\alpha = 0.810$), perceived usefulness (four items, $\alpha = 0.861$), perceived ease of use (three items, $\alpha = 0.791$), and behavioral intention to use ChatGPT (four items, $\alpha = 0.873$). All scale items were adapted from previously established instruments in prior research (Davis, 1989; Davis & Venkatesh, 1996; Huang et al., 2021; Khlaisang et al., 2023; Teo, 2015; Teo et al., 2018; Teo et al., 2019).

To ensure linguistic and conceptual equivalence, the items underwent a translation and back-translation process. First, a bilingual scholar translated the items from English into Turkish. Then, an independent bilingual expert performed a back-translation into English without access to the original version. Discrepancies between the two versions were reviewed and resolved to improve clarity. The final questionnaire included 30 items (see Appendix).

The questionnaire was further reviewed through expert evaluation and pilot testing. A panel of three specialists in educational technology and teacher education evaluated the items for clarity, cultural appropriateness, and conceptual alignment. Based on their feedback, minor revisions were made to refine wording and contextual relevance. Subsequently, a pilot test was conducted with 20 pre-service teachers who were not part of the main sample. Feedback confirmed the clarity and usability of the instrument" is slightly too definitive with a 20-participant pilot. Feedback confirmed the clarity and usability of the instrument, supporting its readiness for large-scale data collection.

Data Analysis

Structural equation modeling (SEM) was conducted using the lavaan package in R (Rosseel, 2012) to evaluate the proposed research model. The Maximum Likelihood (ML) estimator assumes multivariate normality (Kline, 2016). This assumption was tested using Mardia's multivariate kurtosis coefficient (Gana & Broc, 2019), which indicated a violation ($b2d$ = 1127.176, z = 59.437, p < .001). Consequently, parameter estimates were obtained using bootstrapping with 1,000 resamples, as recommended by Gana and Broc (2019). Bootstrapping was used to obtain more robust estimates under non-normality and to generate 95% confidence intervals for indirect and total effects.

Given the sensitivity of the chi-square statistic to sample size (Kline, 2016), multiple fit indices and their recommended thresholds were used to assess model adequacy: $\chi^2/df < 3.00$, Comparative Fit Index (CFI) > .90, Tucker–Lewis Index (TLI) > .90, Root Mean Square Error of Approximation (RMSEA) < .08, and Standardized Root Mean Residual (SRMR) < .08 (Hair et al., 2019; Kline, 2016).

The analysis proceeded in two stages. First, the measurement model was evaluated for fit, reliability, and validity. Reliability was assessed using Cronbach's alpha, McDonald's omega, and composite reliability (CR). Convergent validity was examined through average variance extracted (AVE), while discriminant validity was evaluated using the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait–Monotrait (HTMT) ratio of correlations (Henseler et al., 2015). After evaluating the measurement model, the structural model was tested, the structural model was tested to assess overall fit, estimate path coefficients and their statistical significance, and calculate direct, indirect, and total effects. R^2 values were calculated to assess the proportion of variance explained in the endogenous constructs.

Results

Descriptive Statistics

Table 2 presents the descriptive statistics for the latent constructs included in the extended model. All constructs had mean values above the scale midpoint of 3, indicating generally positive perceptions among participants. Notably, constructivist teaching beliefs had the highest mean scores, while the remaining constructs also had mean scores above the scale midpoint. The relatively low standard deviations (all below 1) indicate limited variability in participants' responses. Moreover, the skewness and kurtosis values were within acceptable limits, indicating no substantial departures from univariate normality (Kline, 2016).

Table 2. *Descriptive Statistics of the Latent Constructs*

Construct	Items	Mean	SD	Skewness	Kurtosis
Subjective norm	3	3.656	0.729	-0.149	0.149
Constructivist teaching beliefs	5	4.643	0.453	-1.496	1.889
ChatGPT self-efficacy	4	3.537	0.655	0.281	0.033
Perceived enjoyment	3	4.045	0.639	-0.038	-0.803
Facilitating conditions	3	4.180	0.663	-0.454	-0.061
Perceived usefulness	4	4.096	0.657	-0.242	-0.576
Perceived ease of use	3	3.955	0.640	-0.490	0.615
Behavioral intention	4	3.851	0.642	0.379	-0.791

Evaluation of the Measurement Model

Confirmatory factor analysis (CFA) was conducted to assess the measurement model. The model demonstrated a good fit to the data ($\chi^2 = 828.753$, df = 349, $p < .001$; $\chi^2/df = 2.375$; CFI = .939; TLI = .929; RMSEA = .053, 90% CI [.048, .058]; SRMR = .054). Following the CFA, reliability and validity were examined. As shown in Table 3, Cronbach's alpha (α), McDonald's omega (ω), and composite reliability (CR) values for all latent constructs exceeded the recommended threshold of 0.70 (Hair et al., 2019). Furthermore, all standardized factor loadings were significant ($p < .001$) and ranged from 0.607 to 0.886, providing support for the measurement model. Convergent validity was supported, with all AVE values exceeding the recommended threshold of .50 (Hair et al., 2019).

Table 3. *Reliability and Convergent Validity for the Measurement Model*

Constructs	Items	Standardized Factor Loadings
Subjective Norm (α = 0.795, CR = 0.797, ω = 0.797, AVE =0.567)	SN1	0.716***
	SN2	0.822***
	SN3	0.720***
Constructivist Teaching Beliefs (α = 0.862, CR = 0.865, ω = 0.862, AVE =0.565)	CTB1	0.607***
	CTB2	0.749***
	CTB3	0.832***
	CTB4	0.856***
	CTB5	0.706***
ChatGPT Self-Efficacy (α = 0.844, CR = 0.855, ω = 0.855, AVE =0.603)	CSE1	0.662***
	CSE2	0.668***
	CSE3	0.851***
	CSE4	0.857***
Perceived Enjoyment (α = 0.895, CR = 0.896, ω = 0.898, AVE =0.743)	PE1	0.845***
	PE2	0.853***
	PE3	0.886***
Facilitating Conditions (α = 0.810, CR = 0.822, ω = 0.823, AVE =0.613)	FC1	0.857***
	FC2	0.821***
	FC3	0.640***
Perceived Usefulness (α = 0.861, CR = 0.870, ω = 0.876, AVE =0.630)	PU1	0.819***
	PU2	0.670***
	PU3	0.847***

	PU4	0.798***
Perceived Ease of Use (α = 0.791, CR = 0.795, ω = 0.797, AVE =0.566)	PEU1	0.706***
	PEU2	0.707***
	PEU3	0.837***
Behavioral Intention to use ChatGPT (α = 0.873, CR = 0.880, ω = 0.885, AVE =0.650)	BI1	0.837***
	BI2	0.853***
	BI3	0.847***
	BI4	0.660***

Note. *** p <.001

The discriminant validity of the measurement model was evaluated using two well-established approaches: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. According to the Fornell-Larcker criterion, the square root of the average variance extracted (AVE) for each construct should exceed its correlations with other constructs (Fornell & Larcker, 1981). For HTMT, values below .85 were considered indicative of adequate discriminant validity (Henseler et al., 2015). As shown in Table 4, both criteria were satisfied, providing support for the discriminant validity of the measurement model.

Table 4. *Discriminant Validity for the Measurement Model*

Criteria		SN	CTB	CSE	PE	FC	PU	PEU	BI
Fornell-Larcker	SN	(0.753)							
	CTB	0.154	(0.752)						
	CSE	0.338	0.209	(0.777)					
	PE	0.474	0.325	0.605	(0.862)				
	FC	0.350	0.020	0.252	0.206	(0.783)			
	PU	0.495	0.261	0.563	0.771	0.236	(0.794)		
	PEU	0.320	0.218	0.656	0.588	0.198	0.556	(0.752)	
	BI	0.536	0.156	0.535	0.558	0.258	0.677	0.458	(0.806)
HTMT	SN								
	CTB	0.183							
	CSE	0.333	0.293						
	PE	0.505	0.407	0.652					
	FC	0.391	0.033	0.260	0.242				
	PU	0.518	0.342	0.622	0.828	0.253			
	PEU	0.325	0.252	0.696	0.630	0.221	0.606		
	BI	0.583	0.212	0.587	0.647	0.299	0.763	0.509	

Note. SN=Subjective Norm; CTB=Constructivist Teaching Beliefs; CSE=ChatGPT Self-efficacy; PE=Perceived Enjoyment; FC=Facilitating Conditions; PU=Perceived Usefulness; PEU=Perceived Ease of Use; BI= Behavioral Intention to Use ChatGPT.

Analysis of the Structural Models

After establishing adequate reliability and validity of the measurement model, the structural model was tested using SEM. The model demonstrated an acceptable fit to the data (χ^2 = 933.494, df = 356, p < .001; χ^2/df = 2.622; CFI = .927; TLI = .916; RMSEA = .058, 90% CI [.053, .062]; SRMR = .061).

Table 5 summarizes the results of the hypothesis testing. Eight of the eleven proposed hypotheses were supported. Specifically, perceived usefulness (PU; β = 0.424), subjective norm (SN; β = 0.260), and ChatGPT self-efficacy (CSE; β = 0.230) showed the strongest association with behavioral intention (BI), supporting H1, H5, and H8. Among these, PU was positively associated with BI. In contrast, perceived ease of use (PEU; β = –0.015) and perceived enjoyment (PE; β = –0.005) were not significantly associated with BI, thus H3 and H10 were not supported. Regarding predictors of PU, PEU (β = 0.520), SN (β = 0.332), and constructivist teaching beliefs (CTB; β = 0.099) were significant, supporting H2, H4, and H6. For PEU, CSE (β = 0.461) and PE (β = 0.389) were significant predictors, whereas facilitating conditions (FC; β = 0.017) were not, supporting H7 and H9 but H11 was not supported. The structural model explained 54% of the variance in BI, 55% of the variance in PU, and 59% of the variance in PEU.

Table 5. Hypotheses Testing Results

Hypotheses	Path	B	β	SE	*z*-value	Results
H1	PU → BI	0.395	0.424 [0.275, 0.568]	0.072	5.502***	Supported
H2	PEU → PU	0.600	0.520 [0.360, 0.681]	0.098	6.099***	Supported
H3	PEU → BI	-0.016	-0.015 [-0.210, 0.164]	0.105	-0.154	Not supported
H4	SN → PU	0.365	0.332 [0.193, 0.463]	0.084	4.351***	Supported
H5	SN → BI	0.266	0.260 [0.149, 0.380]	0.065	4.125***	Supported
H6	CTB → PU	0.190	0.099 [0.015, 0.177]	0.081	2.338*	Supported
H7	CSE → PEU	0.521	0.461 [0.314, 0.606]	0.084	6.209***	Supported
H8	CSE → BI	0.279	0.230 [0.061, 0.384]	0.101	2.774**	Supported
H9	PE → PEU	0.360	0.389 [0.218, 0.563]	0.084	4.304***	Supported
H10	PE → BI	-0.005	-0.005 [-0.159, 0.156]	0.077	-0.068	Not supported
H11	FC → PEU	0.016	0.017 [-0.065, 0.099]	0.039	0.411	Not supported

Note. * $p < .05$; ** $p < .01$; *** $p < .001$; B = Unstandardized path coefficient; β = Standardized path coefficient; SE = Standard Error. SN=Subjective Norm; CTB=Constructivist Teaching Beliefs; FC=Facilitating Conditions; CSE=ChatGPT Self-efficacy; PE=Perceived Enjoyment; PU=Perceived Usefulness; PEU=Perceived Ease of Use; BI= Behavioral Intention to Use ChatGPT. The values in square brackets are the 95% confidence interval values of the standardized beta coefficient.

To assess the magnitude of the relationships among the constructs, standardized direct, indirect, and total effects were calculated. A direct effect represents the immediate relationship between two constructs, whereas an indirect effect represents the relationship between two constructs through one or more intervening variables. The total effect is the sum of both direct and indirect effects. Following Cohen's (1988) guidelines, standardized path coefficients of 0.10, 0.30, and 0.50 indicate small, medium, and large effect sizes, respectively. These results are presented in Table 6.

Subjective norm (SN; β = 0.401) showed the largest statistically significant total effect on behavioral intention (BI). CSE had a total effect of (CSE) β = 0.331, with indirect effects operating through PEU (β = 0.205), PU (β = 0.223), and CTB (β = 0.042). The total effects of perceived enjoyment (PE) and facilitating conditions (FC) on BI were not significant.

For perceived usefulness (PU), both CSE (β = 0.239) and PE (β = 0.203) demonstrated significant indirect and total effects, whereas FC (β = 0.011) did not. Regarding indirect effects on BI, PEU (β = 0.220) showed the largest influence, followed by SN (β = 0.141), CSE (β = 0.101 via PEU and PU), PE (β = 0.086 via PEU and PU), and CTB (β = 0.042). Indirect effects of FC on BI were not statistically significant.

Table 6. Direct, Indirect and Total Effects of Predictors

Construct	Predictor	Standardized estimates (β)		
		Direct	Indirect	Total
PU	FC (FC→PEU→PU)	-	0.011 [-0.026, 0.053]	0.011 [-0.026, 0.053]
	CSE (CSE→PEU→PU)	-	0.239 [0.156, 0.331]***	0.239 [0.156, 0.331]***
	PE (PE→PEU→PU)	-	0.203 [0.085, 0.363]**	0.203 [0.085, 0.363]**
BI	SN (SN→PU→BI)	0.260***	0.141 [0.072, 0.216]***	0.401 [0.295, 0.516]***
	CTB (CTB→PU→BI)	-	0.042 [0.007, 0.079]*	0.042 [0.007, 0.079]*
	CSE (CSE→PEU→BI)	0.230**	-0.007 [-0.094, 0.089]	0.223 [0.108, 0.338]***
	CSE (CSE→PEU→PU→BI)	0.230**	0.101 [0.053, 0.164]***	0.331 [0.174, 0.507]***
	PE (PE→PEU→BI)	-0.005	-0.006 [-0.106, 0.067]	-0.011 [-0.166, 0.118]
	PE (PE→PEU→PU→BI)	-0.005	0.086 [0.032, 0.181]*	0.081 [-0.062, 0.248]
	FC (FC→PEU→BI)	-	-0.000 [-0.011, 0.009]	-0.000 [-0.011, 0.009]
	FC (FC→PEU→PU→BI)	-	0.005 [-0.011, 0.024]	0.005 [-0.011, 0.024]
	PEU (PEU→PU→BI)	-0.015	0.220 [0.122, 0.359]***	0.205 [0.028, 0.389]*

Note. * $p < .05$; ** $p < .01$; *** $p < .001$; SN=Subjective Norm; CTB=Constructivist Teaching Beliefs; FC=Facilitating Conditions; CSE=ChatGPT Self-efficacy; PE=Perceived Enjoyment; PU=Perceived Usefulness; PEU=Perceived Ease of Use; BI= Behavioral Intention to Use ChatGPT. The values in square brackets are the 95% confidence interval values of the standardized beta coefficient.

Discussion

Overview of the Research Model

This study tested an extended TAM to explain pre-service teachers' intentions to use ChatGPT in Türkiye. The model accounted for a substantial share of variance in behavioral intention and provided support for most relationships proposed in the original TAM, with one notable exception: the direct path from PEU to BI was not supported. Instead, PU emerged as the strongest predictor of BI, while PEU contributed indirectly via PU. SN and CSE also showed significant direct associations with BI, whereas PE was indirectly associated with BI through PEU and PU. CTB enhanced PU and, consequently, indirectly supported BI, whereas FC were not significantly associated with PEU. Consequently, the explained variance (R^2) values indicate that PU, SN, and CSE accounted for 54% of the variance in BI. PEU, SN, and CTB explained 55% of the variance in PU, while CSE and PE explained 59% of the variance in PEU, as illustrated in Figure 3.

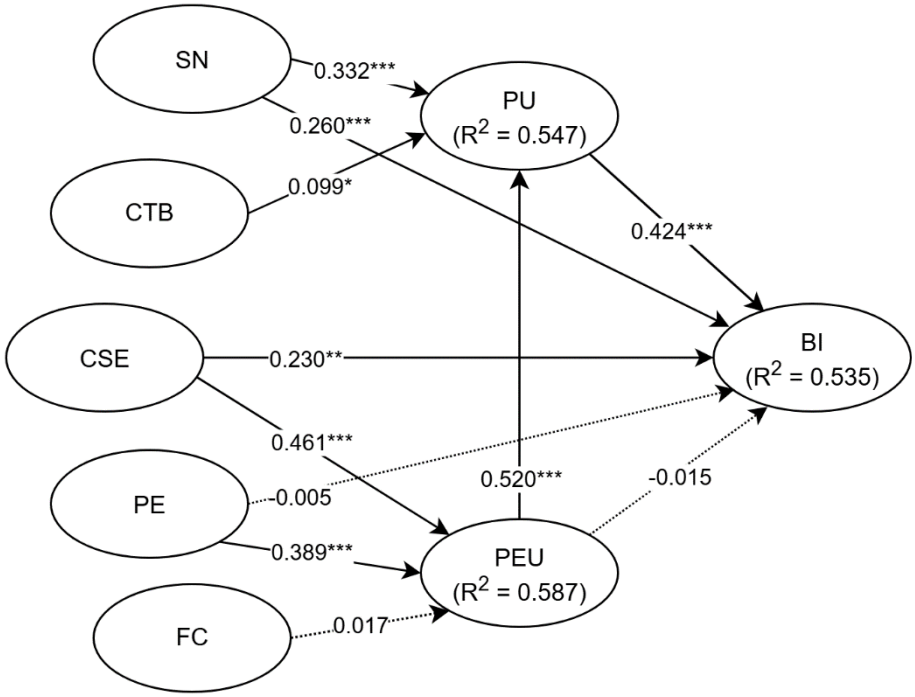


Figure 3. *Standardized Path Coefficients of the Research Model*

The Dominance of Perceived Usefulness and Subjective norms

The extended TAM supported all relationships established in the original model (Davis & Venkatesh, 1996), with the exception of the direct path from PEU to BI. Consistent with prior research (Gökçearslan et al., 2022; Zhang, 2023), PU showed the strongest direct association with BI, while PEU was indirectly associated with BI through PU. This finding suggests that perceived ease of use alone may not be sufficient to explain pre-service teachers' behavioral intentions. Therefore, teacher educators should design activities such as formative feedback and differentiated planning, that make this value explicit in authentic tasks.

SN significantly influenced both PU and BI, yielding the highest total effect on the latter. Given the strong association observed for SN, teacher education programs may consider fostering communities of practice and peer-mentoring structures that support responsible GenAI use. While this aligns with various Web 2.0 contexts (Teo et al., 2019; Zhang et al., 2023), it diverges from studies reporting negligible SN effects (Mei et al., 2018), highlighting that the role of subjective norms may vary across technologies and educational contexts.

The Role of Self-Efficacy and Pedagogical Beliefs

CSE positively predicted both PEU and BI, reinforcing the importance of self-perceived competence in understanding intentions to use ChatGPT (Sun et al., 2025; Zhang et al., 2023). However, the presence of null effects in subject-specific literature (e.g., mathematics; Gurer, 2021) suggests that the relationship between CSE and BI may vary across disciplinary contexts. In the current study, the findings regarding CSE suggest potential value in scaffolded practice and micro-teaching sessions focused on GenAI skills, such as prompt design and critical verification.

CTB exerted a direct effect on PU and an indirect effect on BI, supporting previous research linking student-centered pedagogical beliefs with technology acceptance (Huang & Teo, 2021; Acosta-Enriquez et al., 2025). This finding suggests that professional development could align GenAI use with constructivist principles, for example by using ChatGPT as a scaffold for inquiry-based learning.

Enjoyment and Facilitating Conditions: Indirect and Null Effects

Contrary to expectations and previous findings (Sánchez-Prieto et al., 2019; Teo et al., 2019), PE did not directly predict BI. Instead, PE was positively associated with PEU and indirectly associated with BI through PEU and PU. Consequently, these findings suggest that enjoyment may be relevant to behavioral intention primarily through its associations with perceived ease of use and usefulness. The findings may have implications for designing GenAI tools and learning activities that combine engagement with pedagogical value.

Finally, FC did not significantly impact PEU, which contrasts with seminal TAM literature (Aypay et al., 2012; Teo & Milutinovic, 2015; Venkatesh & Bala, 2008). One possible explanation is that participants may have perceived the available digital infrastructure as adequate; however, this interpretation requires further investigation. The nonsignificant finding suggests that facilitating conditions may have been less salient for this particular group of pre-service teachers. Universities may therefore consider complementing technical support with pedagogical and motivational support for GenAI use.

Implications of the Study

Theoretical Implications

Theoretically, this study extends the TAM framework by integrating domain-specific constructs, Constructivist Teaching Beliefs (CTB), ChatGPT Self-efficacy (CSE), and Subjective Norms (SN), to provide a context-sensitive model for GenAI adoption in teacher education. A key theoretical insight lies in the realignment of core TAM drivers: while PU remains the strongest predictor, the non-significant direct paths of PEU and PE suggest that cognitive ease and enjoyment operate primarily as experience suggest that perceived ease of use and enjoyment may be indirectly associated with behavioral intention through perceived usefulness. Furthermore, by showing that CTB was positively associated with PU, this study extends the belief-technology alignment literature, suggesting a potential alignment between learner-centered pedagogical beliefs and perceptions of technology usefulness. Finally, the dominant influence of SN highlights the importance of social influences in pre-service teachers' intentions to use GenAI. Collectively, these findings highlight the value of incorporating both pedagogical beliefs and social influences into technology acceptance models in teacher education.

Practical Contribution

From a practical perspective, these findings offer tentative implications for teacher education programs to foster the pedagogically sound and responsible integration of GenAI. Given the importance of CSE in the model, institutions could embed collaborative micro-teaching and hands-on activities within coursework to provide pre-service teachers with opportunities to build confidence in using GenAI for pedagogical purposes. Furthermore, given the association between SN and behavioral intention, programs could encourage peer mentoring and collaborative communities of practice to support responsible GenAI use.

Crucially, these initiatives must move beyond mere usage optimization to critically address the socio-technical challenges of responsible GenAI. Institutional verification procedures and ethical guidelines may also help prepare pre-service teachers to critically evaluate issues such as hallucinations, algorithmic bias, and data privacy. Positioning ChatGPT as a critical cognitive scaffold rather than a replacement for teachers may help maintain an emphasis on teacher agency, equity, and critical digital literacy.

Limitations and Recommendations for Future Research

Despite its contributions, this study has several limitations that provide avenues for future research. First, the sample was restricted to pre-service teachers in Türkiye, limiting generalizability to different cultural or educational systems. Future cross-cultural studies could examine whether these findings are consistent across different educational and cultural contexts. Second, the cross-sectional nature of the data precludes definitive causal inferences; longitudinal designs could help examine how these perceptions change over time as GenAI becomes more routinely integrated into teacher education. Third, although the model explained 54% of the variance in behavioral intention, the remaining unexplained variance suggests that additional factors may also contribute to behavioral intention. Future models could incorporate additional factors such as GenAI anxiety, algorithmic trust, and perceived risk. Fourth, reliance on self-reported measures may introduce bias; incorporating objective data (e.g., system logs or observations) would enhance empirical precision. Fifth, while participants' academic disciplines were documented, subgroup analyses were omitted due to sample size constraints within certain programs. Because subject-specific demands (e.g., mathematics, science, or language education) may shape self-efficacy and pedagogical beliefs differently across disciplines. Finally, as ChatGPT continues to evolve, future research should periodically reassess the relevance of existing acceptance frameworks in light of changing GenAI capabilities.

Conclusion

This study tested an extended TAM to explain pre-service teachers' behavioral intentions to use ChatGPT in Türkiye, highlighting the importance of cognitive, social, and pedagogical factors in understanding intentions to use GenAI. The findings demonstrate that technical usability (PEU) and intrinsic enjoyment (PE) do not directly foster behavioral intention; instead, PU, SN, and CSE showed significant associations with behavioral intention, while CTB was positively associated with PU. However, Given the cross-sectional, self-report design, these relationships should not be interpreted as causal. Teacher education programs may therefore benefit from combining the development of perceived usefulness with critical digital literacy and verification practices. Pre-service teachers' perceptions of usefulness must be balanced with critical digital literacy and verification practices to counteract GenAI hallucinations, algorithmic biases, and data privacy vulnerabilities. Furthermore, to prevent overreliance from undermining student autonomy and teacher agency, ChatGPT should be positioned as a cognitive scaffold rather than an autonomous pedagogical replacement. Future longitudinal research incorporating additional factors such as algorithmic trust and perceived risk could provide a more comprehensive understanding of responsible and pedagogically sound GenAI integration.

Declarations

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Data availability: *The data that support the findings of this study are available from the corresponding author upon reasonable request.*

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Appendix

Table 7. List of Constructs and Corresponding Items

Constructs	Items	English
Subjective Norm (SN)	SN1	People who are important to me support me to use ChatGPT in teaching.
	SN2	My students will support my use of ChatGPT in teaching.
	SN3	Schools support the use of ChatGPT in teaching.
Constructivist Teaching Beliefs (CTB)	CTB1	The focus of teaching is to help students construct knowledge from their learning experience instead of knowledge delivery.
	CTB2	Good teachers always make their students feel important.
	CTB3	Every student is unique or special and deserves an education tailored to his or her particular needs.
	CTB4	Learning means students have ample opportunities to explore, discuss and express their ideas.
	CTB5	It is important that a teacher understands the feelings of the students.
ChatGPT Self-efficacy (CSE)	CSE1	I feel at ease using ChatGPT.
	CSE2	I know enough to use ChatGPT.
	CSE3	I am sure of my abilities to use ChatGPT effectively.
	CSE4	I am confident with my abilities to select appropriate ChatGPT prompts for teaching.
Perceived Enjoyment (PE)	PE1	The process of using ChatGPT in teaching will be pleasant.
	PE2	Using ChatGPT in teaching will arouse my curiosity.
	PE3	Using ChatGPT in teaching will be exciting.
Facilitating Conditions (FC)	FC1	When I need help to learn to use ChatGPT in teaching, someone will be there to teach me.
	FC2	I will have the resources necessary to teach with the ChatGPT.
	FC3	Training for using ChatGPT in teaching will be available for me.
Perceived Usefulness (PU)	PU1	Using ChatGPT will improve my teaching performance.
	PU2	Using ChatGPT will enhance my teaching effectiveness.
	PU3	Using ChatGPT will increase my productivity in my teaching.
	PU4	ChatGPT will be useful for my teaching.
Perceived Ease of Use (PEU)	PEU1	Using ChatGPT in teaching will be clear and understandable.
	PEU2	Using ChatGPT in teaching will be flexible to interact with.
	PEU3	It will be easy to become skillful at using ChatGPT in teaching.
Behavioral Intention to use ChatGPT (BI)	BI1	I will use ChatGPT in my future teaching.
	BI2	I plan to use ChatGPT often in my future teaching.
	BI3	I will talk about the positive aspects of using ChatGPT in my future classroom.
	BI4	I will recommend ChatGPT to my future colleagues.