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|Research Article / Araştırma Makalesi|

Determinants of Higher Education Students' Use of Generative AI Chatbots: An Extended Technology Acceptance Model (TAM) Perspective

Yüksek Öğretim Öğrencilerinin Üretken Yapay Zekâ Sohbet Robotlarını Kullanımının Belirleyicileri: Genişletilmiş Teknoloji Kabul Modeli (TKM) Bakış Açısı

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Keywords

Generative artificial intelligence (Gen-AI)

Technology acceptance model (TAM)

Trust

Individual impact

Higher education

Abstract

This study investigates the factors influencing higher education students' self-reported use of generative AI (Gen-AI) chatbots through an extended Technology Acceptance Model (TAM). The model incorporates trust and individual impact alongside perceived usefulness and perceived ease of use to better explain students' adoption behavior. Usage is defined as the self-reported frequency of chatbot use rather than post-adoption continuance intention. A quantitative, cross-sectional survey was conducted with 303 higher education students. Data were analyzed using Structural Equation Modeling (SEM) in Smart-PLS after confirming the reliability and validity of the measurement model. It's shown that perceived ease-of-use significantly affects both perceived usefulness and self-reported usage. Perceived usefulness also positively influences usage frequency. Trust shapes students' perceptions of ease of use and usefulness but does not directly affect usage. Moreover, usage has a strong positive impact on individual outcomes, indicating academic and personal benefits associated with frequent use. Ease of use and perceived usefulness are the key drivers of students' Gen-AI use. Trust influences adoption indirectly by shaping these perceptions. Sustained use of these tools enhances academic and personal outcomes, and the extended TAM proves to be a suitable framework for explaining Gen-AI adoption in higher education contexts.

Anahtar Sözcükler

Üretken yapay zekâ

Teknoloji kabul modeli (TKM)

Güven

Bireysel etki

Yüksek öğretim

Öz

Bu çalışma, genişletilmiş bir Teknoloji Kabul Modeli (TKM) aracılığıyla, yükseköğretim öğrencilerinin üretken yapay zekâ (Gen-AI) sohbet robotlarını kendi bildirimlerine göre kullanmalarını etkileyen etmenleri araştırmaktadır. Model, öğrencilerin benimseme davranışlarını daha iyi açıklamak için algılanan yarar ve algılanan kullanım kolaylığının yanı sıra güven ve bireysel etkiyi de içermektedir. Kullanım, benimseme sonrası devam etme niyeti yerine, sohbet robotu kullanımının kendi bildirimlerine göre sıklığı olarak tanımlanmıştır. 303 yükseköğretim öğrencisiyle nicel, kesitsel bir anket çalışması yapılmıştır. Veriler, ölçüm modelinin güvenilirliği ve geçerliliği doğrulandıktan sonra Smart-PLS'de Yapısal Eşitlik Modellemesi (YEM) kullanılarak analiz edilmiştir. Algılanan kullanım kolaylığının hem algılanan yararı hem de gerçek kullanımı önemli ölçüde etkilediği gösterilmiştir. Algılanan yarar ayrıca kullanım sıklığını da olumlu yönde etkilemektedir. Güven, öğrencilerin kullanım kolaylığı ve yarar algılarını şekillendirmekte ancak kullanımı doğrudan etkilememektedir. Üstelik kullanımın bireysel sonuçlar üzerinde güçlü bir olumlu etkisi vardır ve sık kullanımla ilişkili akademik ve kişisel yararı ortaya koymaktadır. Kullanım kolaylığı ve algılanan yarar, öğrencilerin üretken yapay zekâyı kullanmalarının temel belirleyicileridir. Güven, bu algıları şekillendirerek dolaylı olarak benimsemeyi etkilemektedir. Bu araçların sürekli kullanımı akademik ve kişisel sonuçları iyileştirmekte ve genişletilmiş TKM, yükseköğretim bağlamlarında üretken yapay zekânın benimsenmesini açıklamak için uygun bir çerçeve olduğunu kanıtlamaktadır.

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Introduction

Generative Artificial Intelligence (hereafter Gen-AI) is rapidly transforming the landscape of higher education, offering novel opportunities for personalized learning and innovative assessment methods. Among the diverse Gen-AI applications, AI-driven conversational agents—commonly referred to as chatbots (hereafter chatbots)—play a particularly prominent role in supporting student learning by generating personalized content, adaptive exercises, and interactive simulations. These tools are increasingly transforming traditional teaching methods and enriching the learning experience (Kumar et al., 2025).

The integration of chatbots into higher education has significantly transformed conventional pedagogical approaches, altering how students learn, interact, and construct knowledge. Chatbots such as ChatGPT, Copilot, and Gemini are increasingly employed to facilitate personalized learning, provide adaptive feedback, and offer cognitive scaffolding (Al-Kadi & Ali, 2024). As these technologies become more deeply embedded within academic ecosystems, understanding the determinants that influence students' usage of such tools is essential to ensure their sustainable and effective adoption in educational settings (Holzmann, 2025).

Although the Technology Acceptance Model (hereafter TAM) (Davis, 1987; Davis, 1989) and its extended versions have been widely employed to explain users' acceptance of new technologies in various contexts (Gelibolu, 2024; Sharma et al., 2024), their adaptation to chatbot-based educational tools remains limited. Prior research has predominantly focused on general artificial intelligence applications or conventional Learning Management Systems (Castillo-Martínez et al., 2024), often overlooking the distinctive features of chatbots, such as their conversational intelligence, adaptive learning potential, and ability to simulate higher-order cognitive processes (Xue et al., 2025; Heilala et al., 2025). This gap highlights the importance of extending the TAM to more accurately explain students' behavioral intentions and their sustained engagement with these emerging chatbot tools.

To fill this research gap, the current study proposes and empirically tests an extended TAM framework that incorporates trust as a key external construct and individual impact as an outcome variable. Trust is crucial in the adoption of chatbots, as students must rely on AI-generated outputs that may differ in accuracy, ethical considerations, or academic integrity. By integrating trust into the TAM framework, the study aims to examine an extended Technology Acceptance Model in which trust is modelled as an antecedent to perceived ease of use and perceived usefulness, as well as a direct predictor of self-reported usage (hereafter Usage). Furthermore, the study incorporates individual impact as a post-adoption outcome, thereby bridging the adoption-focused TAM literature with outcomes-based perspectives by examining how Usage translates into perceived academic and personal benefits.

This study contributes to the literature on educational technology adoption in multiple ways. Theoretically, it extends the traditional TAM by incorporating trust and individual impact, providing a more comprehensive understanding of students' sustained engagement with chatbot tools in higher education. Unlike many prior studies that focus primarily on a single tool such as ChatGPT, this research considers a broader range of chatbots, including emerging platforms like Gemini, reflecting their increasing accessibility and relevance for students. By integrating trust as a key external construct, the study underscores the importance of students' confidence in AI-generated outputs in shaping perceptions of ease of use and perceived usefulness. The inclusion of individual impact addresses a notable gap in the literature by capturing the individual benefits and learning outcomes students derive from engaging with chatbots, including cognitive, academic, and personal gains. Practically, the findings can guide educators, instructional designers, and policymakers in fostering trustworthy, ethical, and pedagogically effective chatbot integration strategies that enhance learners' academic experience and personal outcomes.

This study aims to examine the role of trust and individual impact in shaping students' perceptions of ease of use and perceived usefulness, and how these perceptions influence their usage (usage frequency) with chatbot-based educational tools in the context of the extended TAM framework. The research was conducted using a quantitative design with a convenience sampling method, and data were collected from 303 higher education students. The collected data were analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM), and the study's hypotheses were subsequently tested using SmartPLS 4.

Based on the findings, the study provides theoretical and practical implications, offering recommendations to researchers and practitioners for the effective, trustworthy, and pedagogically beneficial integration of chatbots in higher education contexts.

Literature Review and Hypotheses Development

In recent years, Turkish higher education institutions have increasingly integrated digital technologies into teaching and learning environments. Following the COVID-19 pandemic, the rapid digital transformation of universities accelerated students' exposure to online learning tools (Gökçearslan et al., 2023). The emergence of generative AI tools such as ChatGPT has further reshaped students' learning practices. This transformation is primarily driven by the transition from passive information consumption to active, personalized interaction with AI agents. In higher education, Gen-AI impacts learning practices by serving as an on-demand tutor that facilitates "scaffolded learning." For instance, research indicates that students utilize these tools for brainstorming, complex concept simplification, and coding assistance, which optimizes their cognitive load (Mollick & Mollick, 2023). Moreover, generative AI influences learning experiences by providing immediate, formative feedback, allowing students to iterate on their assignments in real-time a process previously constrained by limited faculty availability (Su & Yang, 2023).

However, the influence on student experience is dual-faceted. While it enhances self-regulated learning and digital literacy, it also introduces challenges related to "algorithmic dependence" and shifts the focus from rote memorization to critical prompt engineering. Studies have shown that when students use Gen-AI as a collaborative partner rather than a mere answer generator, their perceived individual impact and academic productivity increase significantly (Yan et al., 2024). Consequently, the integration of these tools does not merely supplement existing practices but fundamentally redefines the student's role from a recipient of knowledge to a co-creator of academic content. However, empirical research examining the determinants and outcomes of Gen-AI adoption within the Turkish higher education context remains limited (Karahan Adalı & Bilgili, 2025). This study addresses this gap by focusing on university students in Türkiye.

Generative AI in Higher Education

In the educational context, chatbots are of particular importance due to their potential to transform and enrich learning processes (Kumar et al., 2025). Generative AI (Gen-AI) chatbots are advanced conversational agents powered by Large Language Models (LLMs) that utilize deep learning to generate human-like text, code, and multimedia content based on user prompts (Dwivedi et al., 2023). Within higher education, these tools are generally categorized into general-purpose platforms (e.g., ChatGPT, Google Gemini) and specialized academic assistants designed for literature synthesis and research (e.g., Perplexity AI). Their integration offers significant advantages, such as 24/7 accessibility to personalized learning support, the democratization of quality feedback, and the reduction of cognitive and administrative burdens for students (Baidoo-Anu & Owusu Ansah, 2023).

Particularly in higher education, chatbots hold transformative potential for learning, teaching, and assessment (Yan et al., 2024; Kasneci et al., 2023). Recent studies highlight its diverse capabilities, such as delivering comprehensive feedback, outperforming average students in reflective writing, supporting multimedia learning, and enabling adaptive educational content (Dai et al., 2023; Vartiainen & Tedre, 2023, Wang et al., 2024). Chatbots that engage users through natural language interaction have become valuable tools in higher education (Stöhr et al, 2024). Given their advantages, researching chatbot integration into education provides a broad framework for understanding their impact across diverse contexts. Studies in this area have examined individuals' acceptance of chatbots as novel technologies, employing various theoretical models and frameworks to explain their adoption and use. Recent research highlights how these interactive AI-driven tools support personalized learning, real-time feedback, and academic assistance, enhancing student engagement and learning outcomes (Shahzad et al, 2025; Mustofa et al., 2025; Mirriahi et al., 2025; Kong et al., 2024).

Despite the growing body of research highlighting the pedagogical potential of generative AI tools, less attention has been devoted to understanding the psychological and perceptual mechanisms that drive students' usage behavior. Previous studies (Pitts & Motamedi, 2025; Sio et al., 2025; Tian et al., 2024) primarily highlight performance improvement and engagement outcomes; however, fewer investigations

systematically explore the cognitive and trust-related factors that affect students' acceptance and ongoing interaction with AI-based chatbots. This gap calls for the application and extension of established technology acceptance frameworks in the context of generative AI in higher education.

Technology Acceptance Model

TAM (Davis, 1989) is one of the most widely used frameworks for predicting individuals' intentions to adopt and use technology. TAM focuses on understanding how users accept technology and what factors influence their willingness to use a particular technological system. Grounded in the Theory of Reasoned Action, TAM posits that "perceived usefulness" and "perceived ease of use" shape users' attitudes toward a system, which in turn affect their behavioral intention to use it (Venkatesh & Davis, 2000:187). With the continuous advancement of technology and the emergence of artificial intelligence, the TAM has been increasingly extended to establish a more integrated framework that captures various technological systems (Venkatesh, 2022). Recognizing that technology use is also shaped by social dynamics, recent extensions of TAM have incorporated constructs such as social influence, facilitating conditions, and trust to account for the broader technological context (Venkatesh et al., 2012; Gaber et al., 2023). Early investigations predominantly conducted in the context of computer science, social sciences, business, management, and accounting examined TAM constructs such as system usability, perceived trust, ease of use, e-learning, adoption behavior, e-commerce, and social media engagement (Gupta et al., 2025).In recent years, TAM has become a frequently used theoretical foundation in higher education research, particularly for examining how students and educators accept and adopt AI-powered chatbots (Almogren et al., 2024; Mustofa et al., 2025).

Hypothesis Development

Perceived Ease of Use and Perceived Usefulness

According to the Technology Acceptance Model (TAM), perceived ease of use (PEU) refers to the extent to which an individual believes that using a system requires minimal effort (Davis, 1989, p. 320). In educational settings, PEU reflects whether students perceive a platform as intuitive, easy to navigate, and requiring little technical expertise (Ibrahim & Shiring, 2022). Perceived usefulness (PU), on the other hand, refers to the extent to which an individual believes that using a system enhances their performance (Davis, 1989, p.320). In the context of education, this concept captures students' perceptions that technology supports learning processes, improves efficiency, and facilitates academic tasks (Chen et al., 2025, p. 3).

Empirical research conducted in AI-based educational contexts indicates that both PEU and PU are significant determinants of students' adoption and self-reported usage of generative AI tools (Almogren et al., 2024; Iranmanesh et al., 2022; Yu et al., 2024). In the present study, "usage" is conceptualized as students' self-reported frequency of using Gen-AI chatbots (e.g., daily or frequent use). Unlike post-adoption or expectation-confirmation frameworks that focus on continuance intention, this study follows the traditional TAM perspective by examining realized usage behavior as a behavioral outcome of perceived usefulness and perceived ease of use. Specifically, PEU is expected to enhance PU by reducing the cognitive effort required to use the system, whereas PU drives self-reported usage by highlighting the value of technology in improving learning outcomes (Malik et al., 2021; Choudhury & Shamszare, 2023; Chen et al., 2025).

The adoption of generative AI tools has also gained significant traction in the Turkish higher education context. Recent empirical studies support the theoretical relationships proposed by TAM across different academic disciplines. For example, Büyükeke (2025) examined student acceptance of generative AI tools in programming courses and found that perceived usefulness and perceived ease of use are critical determinants of adoption among students in technical fields. This finding is reinforced by the systematic review conducted by Özgül (2026), which highlights that Gen-AI tools in programming education enhance student engagement and learning performance through their intuitive interfaces and practical benefits. Similarly, Göküş and Yılmaz (2025) investigated theology undergraduate students' behavioral intentions regarding chatbot use and demonstrated that even in non-technical disciplines, students' intentions are strongly influenced by the perceived accessibility and usefulness of AI-based systems. Taken together, these studies highlight the cross-disciplinary relevance of TAM variables in the Turkish context and suggest that Turkish students' perceptions align closely with broader global technological trends.

Based on these theoretical and empirical insights, the following hypotheses are proposed:

H1. PEU positively influences PU.

H2. PEU positively influences students' usage of chatbots.

H3. PU positively influences students' usage of chatbots.

Trust

Trust is a fundamental construct in technology acceptance research, referring to users' belief that a technology can be relied upon to provide accurate, reliable, and impartial information (Wu et al., 2011; Senali et al., 2024). Within the Technology Acceptance Model (TAM), trust has been positioned as an antecedent to perceived ease of use (PEU) and perceived usefulness (PU), shaping users' attitudes and behavioral intentions toward adoption (Gefen et al., 2003; Shin, 2021; Gelibolu & Mouloudj, 2025). By reducing uncertainty and perceived risk, trust enhances users' confidence in interacting with digital systems and strengthens their cognitive evaluations of technological benefits.

In various contexts, empirical research has confirmed the crucial role of trust in new technology acceptance. Trust has been shown to positively influence usage of recommendation systems (Shin, 2020), adoption of online shopping platforms (Gefen et al., 2003), online banking services (Suh & Han, 2002), social networking sites (Sledgianowski & Kulviwat, 2009), and health applications (Beldad & Hegner, 2018). These findings indicate that trust consistently strengthens users' perceptions of usefulness and ease of use, thereby fostering favorable attitudes and realized usage behaviors.

In the context of artificial intelligence systems, trust assumes heightened importance due to the opaque and autonomous nature of algorithmic decision-making. Unlike traditional information systems, generative AI tools operate through complex machine learning architectures that are often non-transparent to users. Research on trust in automation suggests that when systems generate probabilistic or uncertain outputs, users rely heavily on perceived reliability and credibility to reduce cognitive risk (Lee & See, 2004; Glikson & Woolley, 2020). In educational environments—where the accuracy and credibility of information directly affect academic performance—trust becomes a critical mechanism for mitigating epistemic uncertainty and facilitating acceptance of AI-supported learning tools (Kasneci et al., 2023; Ofosu-Ampong et al., 2023).

Although trust has only recently begun to be systematically examined in educational AI contexts, emerging studies suggest that it functions as a precursor to perceived ease of use, perceived usefulness, and adoption of intelligent learning systems (Parsonage et al., 2023; Zhang et al., 2021). In the case of ChatGPT, trust refers to the extent to which students perceive the system as reliable, transparent, and accurate in delivering academic information (Dahri et al., 2025). Factors such as system transparency, reliability, and data security are central to building students' trust in AI-powered educational systems (Ofosu-Ampong et al., 2023). Consequently, students who perceive ChatGPT as trustworthy are more likely to evaluate it as easy to use, useful, and worthy of engagement.

Within extended TAM frameworks, trust is frequently conceptualized not only as an antecedent to PEU and PU but also as a potential direct predictor of usage behavior, particularly in high-uncertainty digital environments (Gefen et al., 2003; Shin, 2021). In generative AI contexts, students may rely directly on their trust judgments when deciding whether to use the system, beyond purely cognitive evaluations of ease and usefulness. Examining both indirect and direct effects of trust therefore provides a more comprehensive understanding of AI adoption in higher education.

Based on these theoretical considerations, the following hypotheses are proposed:

H4: Trust (TR) positively influences PEU.

H5: Trust (TR) positively influences PU.

H6: Trust (TR) positively influences usage.

Individual Impact

The use of information systems often leads to positive outcomes for individuals, such as improved performance, productivity, and learning, conceptualized as *individual impact* in the Information Systems Success Model (DeLone & McLean, 2003). While the Technology Acceptance Model (TAM) primarily explains determinants of technology adoption, the IS Success Model extends this perspective by linking system use to performance-related outcomes. Integrating these perspectives allows the present study to bridge the adoption and outcome literature.

In educational settings, the integration of digital technologies has been shown to enhance learners' productivity, task performance, and perceived learning effectiveness (Cidral et al., 2018). In the context of generative AI, individual impact refers to the academic and cognitive benefits students perceive as a result of using ChatGPT for learning purposes (Boubker, 2024). Frequent engagement with AI-based tools may facilitate deeper understanding, independent learning, and more efficient task completion.

Empirical findings provide mixed but insightful evidence. Ashraf et al. (2025) report that regular ChatGPT users demonstrate improved academic performance and study efficiency. Similarly, Wang and Fan (2025) find that sustained usage is associated with greater academic preparedness and stronger self-regulated learning behaviors. However, Boubker (2024) observes no significant direct effect of ChatGPT usage on individual outcomes, suggesting that mediating mechanisms such as satisfaction or perceived usefulness may influence this relationship.

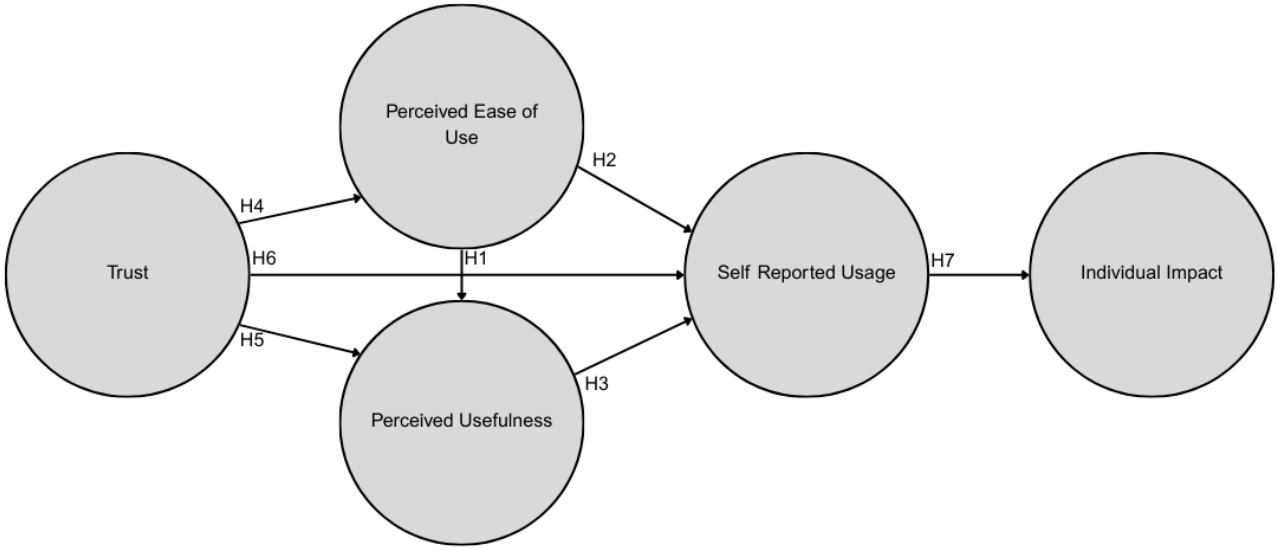
Given this theoretical grounding and empirical evidence, the present study posits that higher levels of usage are positively associated with Individual Impact.

H7: Usage (USE) positively influences Individual impact (IMP).

The research model, grounded in TAM, was derived from the existing literature, as presented in Figure 1

Figure 1

Research Model



Method

Sampling

The sample of this study consisted of 303 higher education students enrolled at Gazi University, a public university in Türkiye. Participants were recruited from five different faculties and two graduate institutes, ensuring representation from diverse academic disciplines within the institution. Sample size adequacy was assessed using a priori power analysis conducted with G*Power (Faul et al., 2009). Using the

F-test family for linear multiple regression (fixed model, R^2 deviation from zero), assuming a medium effect size ($f^2 = 0.15$), a significance level of 0.05, statistical power of 0.95, and three predictors (the maximum number of structural paths directed at an endogenous construct), the required minimum sample size was substantially lower than the actual sample size (N = 303). Therefore, the sample size is considered statistically adequate. A convenience sampling approach was adopted owing to its practicality and accessibility (Lefever et al., 2007). The survey link was disseminated through academic networks, student communication groups, and voluntary sharing channels within the university. No personal contact information was obtained from institutional records or official databases, and participation was entirely voluntary. Data were collected through an online survey designed via Google Forms and distributed through digital communication channels, including WhatsApp and email. This study was approved by the Ethical Commission of Gazi University in accordance with the relevant institutional ethical guidelines (Approval No. E-77082166-604.01-1189515). The data collection process was carried out over a one-month period, beginning on April 15, 2025. Prior to participation, respondents were provided with a detailed explanation of the study's objectives and informed that participation was voluntary, that they could withdraw at any time without penalty, and that their responses would remain anonymous and confidential. A total of 342 responses were initially obtained. After excluding 39 surveys due to missing or inconsistent data, the final dataset consisted of 303 valid responses, which were subsequently used for analysis.

Measures

The questionnaire employed in this research was composed of two main parts, preceded by an introductory section explaining the aim and scope of the study. The first section of the instrument gathered demographic information to contextualize the findings. Specifically, data were collected regarding participants' gender, academic level (undergraduate or graduate), and primary purposes for using Gen-AI chatbots (e.g., research, education, entertainment, or casual conversation). These variables were selected to determine whether the sample represented a diverse range of academic backgrounds and usage habits in higher education. In addition to demographic variables, participants were asked about their general use of generative AI chatbots. In the sample, all participants reported having prior experience using generative AI chatbots, and the usage variable captured the frequency with which students reported interacting with such tools. The second part incorporated measurement instruments assessing individual impact, trust in chatbots, perceived usefulness, perceived ease of use, and actual chatbot usage. All constructs were operationalized using established and validated scales reported in previous studies (Gelibolu, 2024). Individual impact was evaluated through three items adapted from Boubker (2024), while self-reported usage behavior was assessed with three items based on the framework of DeLone and McLean (2003). Perceived usefulness and perceived ease of use were measured using four and three items, respectively, developed by Davis (1989). Trust toward chatbots was assessed using three items adapted from Choung et al. (2023). Participants evaluated the items using a five-point Likert scale, where 1 indicated 'strongly disagree' and 5 indicated 'strongly agree.' To ensure both linguistic and conceptual accuracy, the scales were carefully reviewed. Furthermore, formal permission for the use and adaptation of all measurement scales was obtained from the respective authors or copyright owners to comply with academic ethical standards. "To ensure the linguistic and conceptual accuracy of the scales, a rigorous translation process was followed. Initially, the items were translated into Turkish and then back translated into English by two scholars. The preliminary Turkish translations were reviewed by scholars from Technology Education Department at Hatay Mustafa Kemal University. Afterward, an academician from the Center for Foreign Languages conducted the back-translation. The comparison between the original and the back-translated versions demonstrated a high level of semantic consistency. For further refinement of language quality, the Turkish version of the scale was jointly examined by academicians in the Turkish Education Department, who suggested revisions to enhance clarity and grammatical correctness. Subsequently, the revised instrument was evaluated by experts experienced in psychometric scale development. Prior to the main data collection, a pilot test was administered to a group of 30 participants to identify potential ambiguities or misunderstandings. Based on the feedback received, minor adjustments were applied to improve item comprehensibility. Thus, the finalized survey was administered to the participants. In total, 303 valid responses were obtained and analyzed.

Analysis and Results

Initially, the characteristics of the participant group were summarized through descriptive analyses. Following this step, the validity of the measurement constructs was examined with PLS-SEM. The hypothesis of the research was tested with Smart PLS 4 which is considered appropriate for studies involving small sized samples (Henseler et al., 2015).

Descriptive statistics

As presented in Table 1, the demographic composition of the participants shows a higher representation of female students (68.65%) compared to male students (31.35%). In terms of academic standing, approximately three quarters of the sample consists of undergraduate students (74.92%). The analysis of usage purposes provides critical insights into how students integrate generative AI into their lives. The results indicate that the primary drivers for chatbot engagement are academic and professional; nearly 80% of students utilize these tools for information retrieval/research (79.87%) and education/skill development (79.21%). While a significant portion (42.57%) also engages with chatbots for entertainment, the high frequency of academic-related usage suggests that the participants predominantly view generative AI as a functional educational resource rather than a purely recreational tool. This multi-purpose engagement highlights the versatility of Gen-AI tools in the higher education ecosystem.

Table 1

Descriptive Statistics of Sample

Variable	Category	n	%
Gender	Female	208	68.65
	Male	95	31.35
Academic Level	Undergraduate	227	74.92
	Graduate	76	25.08
Usage Purpose	Information Retrieval / Research	242	79.87
	Education / Skill Development	240	79.21

Additionally, these findings indicate a high level of digital engagement among students, suggesting that they are not only familiar with emerging technologies but also actively integrating them into their learning processes, which may have important implications for educational practices and technology adoption in higher education.

Measurement model assessment

The measurement model was assessed using Partial Least Squares Structural Equation Modeling (PLS-SEM), following established guidelines for variance-based SEM (Hair et al., 2021). Internal consistency reliability, convergent validity, and discriminant validity were systematically evaluated. Indicator reliability was examined through outer loadings. All retained items exceeded the acceptable threshold of 0.50, and the majority surpassed the preferred level of 0.70 (Hair et al., 2021). One item under the Individual Impact construct (IMP3) was removed due to its low factor loading, which fell below the recommended threshold. The removal of this item improved the Average Variance Extracted (AVE) and Composite Reliability (CR) values while preserving the conceptual integrity of the construct. Although the factor loadings of PU1 (0.646) and PU2 (0.660) were slightly below the preferred 0.70 level, they exceeded the acceptable minimum of 0.60 for exploratory and applied research contexts (Hair et al., 2021). The Perceived Usefulness construct demonstrated satisfactory internal consistency (Cronbach's alpha = 0.819; CR = 0.820) and adequate convergent validity (AVE = 0.535 > 0.50). Therefore, these items were retained to preserve content validity, as their removal would not substantially improve model quality.

Convergent validity was confirmed, as all AVE values exceeded the recommended threshold of 0.50 (Bagozzi & Yi, 1988). Internal consistency reliability was supported by Cronbach's alpha values ranging from

0.792 to 0.929 and Composite Reliability values above 0.70 (Fornell & Larcker, 1981; Hair et al., 2021). The results of the measurement model are presented in Table 2.

Table 2

Measurement Model Results

Constructs/Items	FL	CA	CR	AVE
Trust towards Chatbot Use		0.867	0.867	0.685
TR1. I believe that the information provided by Chatbot is trustworthy	0.800			
TR2. The information provided by chatbot is reliable	0.838			
TR3. The information provided by chatbot has integrity	0.843			
Perceived Ease of Use		0.806	0.808	0.584
PEU1. I find chatbots easy to use.	0.794			
PEU2. My interaction with chatbots is clear and easy to understand.	0.781			
PEU3. I find it easy to get chatbots to do what I want it to do	0.716			
Perceived Usefulness		0.819	0.820	0.535
PU1. Using chatbots will improve my learning.	0.646			
PU2. Using chatbots will enhance my effectiveness.	0.660			
PU3. I find chatbots useful tools in my learning.	0.845			
PU4. Using chatbots will save my time.	0.757			
Chatbot Usage		0.929	0.932	0.820
USE1. I use chatbots on daily basis.	0.818			
USE2. I use chatbots frequently.	0.925			
USE3. I visit chatbots often.	0.967			
Individual Impact		0.792	0.800	0.669
IMP1. Chatbots improve my grade for the subject.	0.895			
IMP2.Chatbot use has improved my overall learning performance.	0.733			

Notes: Factor Loading (FL), Cronbach's Alpha (CA), Composite Reliability (CR), Average Variance Extracted (AVE)

Discriminant validity was further assessed using the HTMT criterion. All HTMT values were below the conservative threshold of 0.85(Henseler et al., 2015). Additionally, bootstrapping with 5,000 subsamples (N = 303) was conducted to obtain 95% bias-corrected confidence intervals. None of the upper bounds of the confidence intervals included the value 1.00, confirming that discriminant validity was established (see Table 3).

Table 3

HTMT Ratios with 95% Confidence Intervals

Variables	1	2	3	4	5
1. Perceived Ease of Use					
2. Individual impact	0.546 [0.412–0.668]	—			
3. Perceived Usefulness	0.682 [0.554–0.787]	0.716 [0.615–0.804]	—		
4.Trust	0.493 [0.348–0.614]	0.547 [0.411–0.669]	0.541 [0.415–0.647]	—	
5. Chatbot Usage	0.532 [0.428–0.625]	0.643 [0.527–0.751]	0.541 [0.435–0.638]	0.315 [0.185–0.430]	

Table 3 presents the Heterotrait–Monotrait (HTMT) ratios along with their 95% confidence intervals to assess discriminant validity among the constructs. All HTMT values are below the commonly recommended threshold of 0.85, indicating satisfactory discriminant validity. Furthermore, none of the confidence intervals include the value of 1, which provides additional evidence that the constructs are empirically distinct from each other. These results suggest that each construct captures a unique aspect of the model, supporting the adequacy of the measurement model in terms of discriminant validity.

Model Fit Assessment

The structural model showed acceptable fit (SRMR < 0.10; NFI ≥ 0.80) (Hooper et al., 2008) (see Table 4). In line with current PLS-SEM guidelines (Hair et al., 2021), model fit was further evaluated using SRMR, NFI, and discrepancy measures (d_ULS and d_G). The saturated model demonstrated excellent fit (SRMR = 0.046), while the estimated model yielded SRMR = 0.093, remaining below the recommended 0.10 threshold for variance-based SEM. The NFI value (0.897) approaches the 0.90 benchmark and exceeds the commonly accepted 0.80 adequacy criterion. Additionally, bootstrapping results indicated that the original d_ULS and d_G values were below their respective 95% HI values, suggesting no significant discrepancy between the model-implied and empirical correlation matrices.

Table 4

Structural Model Fit

Fit Indices	Saturated model	Estimated model
SRMR	0.046	0.093
d_ULS	0.252	1.027
d_G	0.138	0.187
Chi-square	218.767	289.692
NFI	0.922	0.897

Common method variance (CMV) was examined using Harman's single-factor test (Podsakoff et al., 2003) and the full collinearity approach (Kock, 2015). With only 42% variance explained by the first factor, CMV does not appear to be an issue. Consistently, the full collinearity test produced VIF values below 3.3 for all constructs, further supporting the absence of common method bias (Kock, 2015). To evaluate the structural model, VIF (multicollinearity), R^2 (explained variance), f^2 (effect size), and Q^2 (predictive relevance) indicators were analyzed (see Table 5). All inner VIF values were under the recommended limit of 5 (Hair et al., 2018), confirming that multicollinearity was not an issue within the model. The R^2 values for the endogenous constructs were 0.240 for perceived ease of use, 0.526 for perceived usefulness, 0.342 for Use, and 0.408 for individual impact. These results indicate that the model explains 24% of the variance in perceived ease of use, 53% of perceived usefulness, 34% of Use, and 41% of Individual Impact.

To assess the explanatory power of the structural model, the effect sizes (f^2) of each significant path were examined. According to Cohen's (1988) guidelines—where f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively—the effect of usage on Individual Impact is very large (f^2 = 0.688), indicating that self-reported system use is a strong determinant of the individual outcomes derived from it. The effect of perceived ease of use on perceived usefulness is large (f^2 = 0.506), suggesting that ease of use plays a substantial role in shaping users' perceptions of usefulness.

The effect of trust on perceived ease of use is medium-to-large (f^2 = 0.316), highlighting that trust contributes notably to how users perceive the simplicity of the system. In contrast, the effect of trust on perceived usefulness is small (f^2 = 0.108), while the effect of perceived ease of use on usage is small (f^2 = 0.072), and the effect of perceived Usefulness on usage is also small (f^2 = 0.083), indicating that although these factors influence system use, their impact remains moderate compared to other pathways in the model. Finally, the effect of trust on actual system use is negligible (f^2 = 0.000), implying that trust does not directly influence actual system use when mediated by other constructs.

The predictive relevance of the model was assessed using the Stone–Geisser Q^2 values obtained via the blindfolding procedure. A Q^2 value greater than zero indicates predictive relevance for a given endogenous construct (Hair et al., 2018). In this study, all endogenous variables showed positive Q^2 values—0.161 for perceived ease of use, 0.198 for perceived usefulness, 0.161 for usage, and 0.116 for Individual Impact—confirming the model's satisfactory predictive performance.

Table 5

Assessment of Structural Model Quality

Constructs	VIF	f2	R2	Q2
Trust -> Perceived Ease of Use	1.000	0.316	0.240	0.161
Usage -> Individual Impact	1.000	0.688	0.408	0.116
Perceived Ease of Use -> Perceived Usefulness	1.316	0.506	0.526	0.198
Trust -> Perceived Usefulness	1.316	0.108		
Perceived Ease of Use -> Usage	1.982	0.072	0.342	0.161
Perceived Usefulness -> Usage	2.109	0.083		
Trust -> Usage	1.457	0.000		

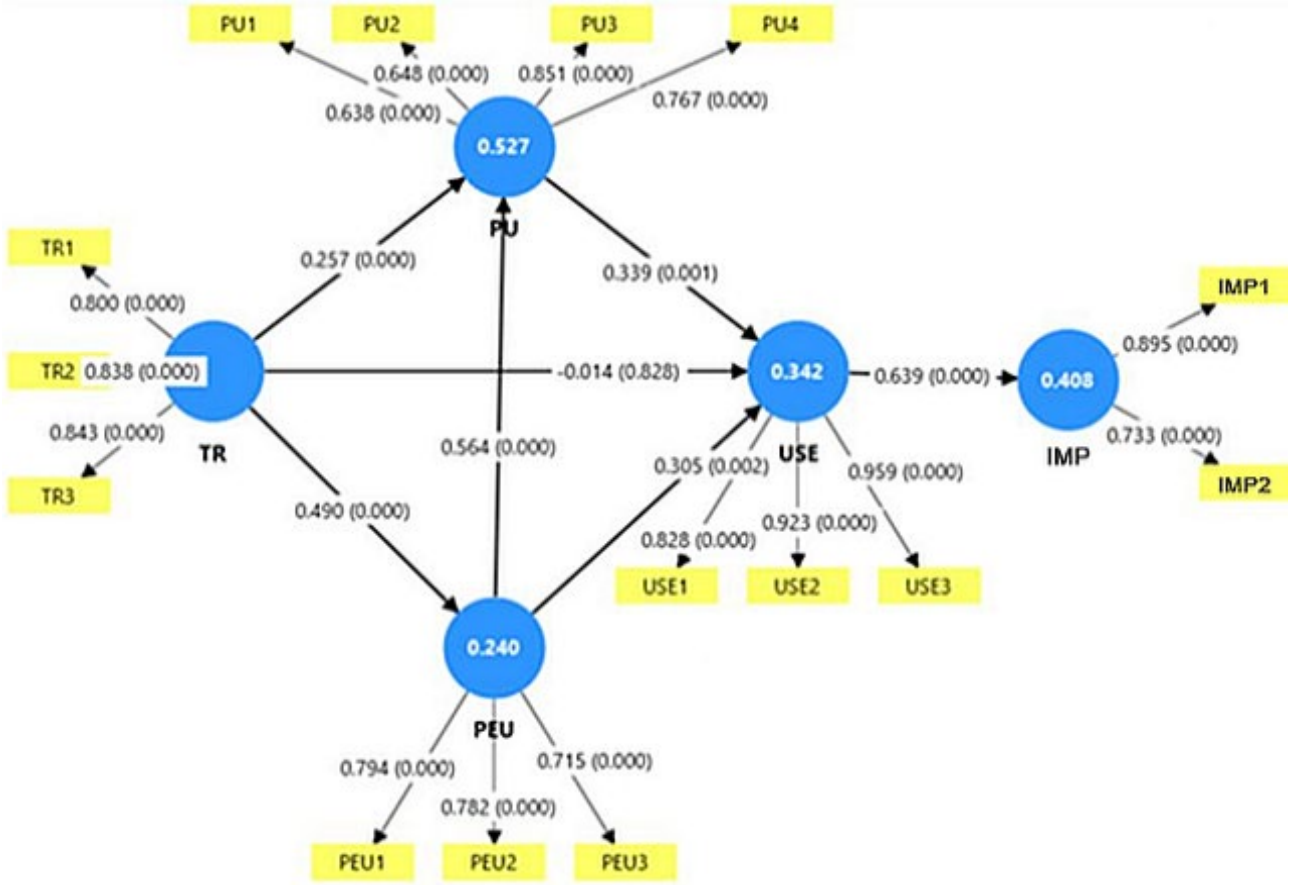
Overall, these findings indicate that explanatory power of research model is strong and predictive accuracy is acceptable. The large and medium effect sizes observed in the key relationships reinforce the robustness of the theoretical framework, suggesting that trust, perceived ease of use, and actual system use are critical determinants of perceived usefulness and individual impact. As demonstrated in Table 5, Q^2 scores which are above zero further confirm that the endogenous constructs in the model possess predictive capability.

Findings

The structural model was assessed through analyses conducted in Smart PLS version 4. To assess the significance of path coefficients and indicator loadings, a bootstrapping procedure with 10,000 resamples was employed. The results of the structural model analysis are demonstrated in Figure 2 and Table 6. The results showed that perceived ease of use (PEU) significantly affected perceived usefulness (PU) ($\beta = 0.564$, $t = 8.109$, $p < 0.001$), supporting H1. In addition, PEU had a direct effect on self-reported usage (USE) ($\beta = 0.305$, $t = 3.093$, $p = 0.002$), thus H2 was supported. The analysis further indicated that perceived usefulness (PU) significantly affected usage ($\beta = 0.339$, $t = 3.424$, $p = 0.001$), supporting H3. Moreover, trust (TR) significantly affected PEU ($\beta = 0.490$, $t = 7.115$, $p < 0.001$) and significantly affected PU ($\beta = 0.257$, $t = 4.083$, $p < 0.001$); therefore, both H4 and H5 were supported. However, the direct effect of TR on USE was not significant ($\beta = -0.014$, $t = 0.217$, $p = 0.828$), meaning H6 was not supported. Finally, the results demonstrated that self-reported usage (USE) had a strong positive effect on Individual impact (IMP) ($\beta = 0.639$, $t = 11.232$, $p < 0.001$), which supports H7. To further explore the non-significant direct effect of trust on self-reported usage (H6), specific indirect effects were examined via bootstrapping to test for mediation. The results revealed that trust exerts a significant indirect influence on self-reported usage through three distinct paths: via PEU ($\beta = 0.150$, $p = 0.006$), via PU ($\beta = 0.087$, $p = 0.015$), and through a serial mediation involving both PEU and PU ($\beta = 0.094$, $p = 0.006$). The combination of significant indirect effects and a non-significant direct path provide empirical evidence for a full mediation mechanism. This suggests that trust acts as a foundational "perceptual scaffolding" that enhances usage not by triggering it directly, but by fostering the necessary cognitive environment where students can appreciate the system's ease and utility.

Figure 2

Structural Model Analyses Results



Following the validation of the measurement model, structural model analysis was conducted to test the proposed theoretical framework and the hypothesized relationships between the constructs. This analysis provides path coefficients and statistical significance levels to determine the direct effects on technology acceptance and usage behavior. The results of the structural model, including the hypothesis testing outcomes, path coefficients, and significance levels, are presented in detail in Table 6.

Table 6

Results of Structural Model

Hypothesis	Path	β	t-value	p-value	Supported
H1	PEU → PU	0.564	8.109	0.000	Yes
H2	PEU → USE	0.305	3.093	0.002	Yes
H3	PU → USE	0.339	3.424	0.001	Yes
H4	TR → PEU	0.490	7.115	0.000	Yes
H5	TR → PU	0.257	4.083	0.000	Yes
H6	TR → USE	-0.014	0.217	0.828	No
H7	USE → IMP	0.639	11.232	0.000	Yes

The structural model results presented in Table 6 provide empirical support for the hypothesized relationships within the proposed framework. The path analysis reveals that Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are significant predictors of students' self reported usage behavior (USE) on generative AI tools. Specifically, the strong positive path coefficient from PEU to PU suggests that when students find these AI platforms intuitive and user-friendly, their perception of the tool's academic utility significantly increases.

Furthermore, the results indicate that Trust plays a critical role in the acceptance process, acting as a foundational element that enhances the individual impact of technology. The significant relationship

between behavioral Intention and self-reported usage behavior confirms that students' positive predispositions toward Gen-AI are effectively translating into regular academic practice. Finally, the positive and significant path toward Individual Impact demonstrates that the integration of these tools contributes tangibly to students' perceived academic performance and productivity. Overall, the model accounts for a substantial proportion of the variance in Gen-AI adoption, validating the relevance of the extended TAM framework in the Turkish higher education context.

Discussion

The results showed that perceived ease of use had a significant positive impact on both perceived usefulness (H1 supported) and self-reported usage (H2 supported), while perceived usefulness also strongly influenced self-reported usage (H3 supported). This relationship can be specifically attributed to the unique conversational affordances of chatbots. Unlike traditional static tools, the natural language processing capabilities of Gen-AI allow for a seamless, dialogue-based interaction that mirrors human communication, thereby significantly reducing the cognitive effort required to operate the system (PEU). Furthermore, the adaptivity of these tools their ability to provide context-aware, personalized responses—directly enhances their utility in an educational setting (PU). As students engage in iterative prompting, the chatbot adapts to their specific learning needs, making the technology feel less like a rigid software and more like a responsive learning partner. This alignment between the system's adaptive features and the users' goal-oriented tasks underscores why PU emerged as the strongest predictor of continued engagement, reinforcing the core tenets of TAM (Davis, 1987) within the specific context of conversational AI. Among these relationships, perceived usefulness emerged as the key driver of self-reported usage (self-reported usage frequency), underscoring its central role within the Technology Acceptance Model (Davis, 1987). These findings are consistent with TAM's foundational assumptions, suggesting that users' perceptions of a system's ease of use indirectly foster usage through enhanced perceptions of usefulness. This outcome also aligns with prior research emphasizing that continued technology usage is primarily driven by the perceived utility of the system in achieving users' goals (Iancu & Iancu, 2023; Agyare et al., 2025).

The results indicated that trust had a significant positive effect on perceived ease of use (H4 supported) and perceived usefulness (H5 supported), but its direct impact on self-reported usage was not significant (H6 not supported). These findings suggest that when students trust AI-based chatbots, they are more likely to find them easy to use and perceive them as useful learning aids, consistent with the assumptions of the Technology Acceptance Model (Davis, 1987). Trust appears to facilitate users' confidence in interacting with the system, thereby reducing uncertainty and enhancing perceptions of ease and usefulness. These findings align with Wu et al. (2011).

Furthermore, the non-significant direct effect of trust on usage (β=-0.014, p=0.828), coupled with its strong influence on PEU (β=0.490, p=0.000) and PU (β=0.257, p=0.000), points to a full mediation mechanism. In this context, trust functions as 'perceptual scaffolding'—a foundational psychological layer that does not directly trigger behavior but creates the necessary cognitive environment for students to appreciate the system's ease and utility. Quantitatively, the influence of trust on engagement is channeled entirely through these TAM constructs, suggesting that without trust as a stabilizing factor, the perceived utility of the AI might not be fully realized by the user.

Beyond its indirect role, trust in generative AI environments may be more appropriately conceptualized as a background condition or enabling antecedent rather than as a direct behavioral driver. In rapidly normalizing AI contexts, students may perceive chatbot usage as instrumental and task-oriented, reducing the salience of trust as a conscious decision factor. In several cases, trust may function as a threshold variable once a minimum level of trust is established, behavioral engagement becomes primarily guided by perceived usefulness and efficiency considerations. This interpretation also helps reconcile contradictory findings in recent AI trust literature. While some studies report a strong direct influence of trust on usage intention in AI systems, others suggest that in highly familiar or utilitarian contexts, trust exerts its influence indirectly through cognitive appraisals such as perceived usefulness or performance expectancy. In educational settings where generative AI tools are increasingly embedded in daily academic routines, trust may operate as a foundational psychological condition that shapes perception formation rather than as a

standalone predictor of actual behavior. Accordingly, the findings of this study contribute to a more differentiated understanding of trust in AI adoption by suggesting that its role may shift depending on contextual familiarity, perceived task relevance, and the normalization of AI technologies.

The results further showed that self-reported usage had a strong and significant effect on individual impact (H7 supported), indicating that students who actively used chatbots experienced higher levels of perceived personal benefit. This relationship reinforces the DeLone & McLean Information Systems Success Model, where system use is a critical precursor to realizing net benefits. In the context of chatbots, the exceptionally high path coefficient suggests that benefits—particularly in self-regulated learning and learning efficiency—are realized through active and iterative engagement rather than passive access. The more frequently and meaningfully students use the tool, the more likely they are to perceive improvements in their academic performance, confidence, and learning efficiency. This result reinforces TAM's assumption that actual system use translates cognitive perceptions (such as usefulness) into tangible outcomes—what can be termed as individual impact or realized benefits (Davis, 1987). Similar findings have been reported in AI-based learning environments, where active use of intelligent systems contributes to improved learning outcomes and user satisfaction (Memon et al., 2022).

Rather than examining platform-specific affordances, this study conceptualizes generative AI chatbots as a broader technological adoption context characterized by conversational intelligence, generative content production, and adaptive epistemic support. In contemporary higher education environments, students frequently interact with multiple AI platforms interchangeably (e.g., ChatGPT, Gemini, Copilot), often selecting tools based on convenience rather than platform-specific features. Therefore, the contribution of this study does not lie in comparing individual platforms, but in theorizing generative AI chatbots as a shared ecosystem of conversational technologies. By focusing on the underlying technological logic of generative AI rather than on individual brand-level differences, the study enhances the generalizability of TAM within rapidly evolving AI environments where platform features continuously evolve.

Theoretical Implications

This study advances the Technology Acceptance Model in the context of generative AI-based educational chatbots in three important ways.

First, rather than merely extending TAM with additional constructs, the study reconceptualizes trust within the unique epistemic characteristics of generative AI systems. Unlike traditional AI or rule-based systems, Gen-AI chatbots actively generate content, co-construct knowledge, and participate in cognitive processes through conversational interaction. In such contexts, trust does not necessarily operate as a direct behavioral driver. Instead, the findings suggest that trust functions primarily as a cognitive enabler that shapes students' perceptions of ease of use and usefulness, which subsequently influences self-reported usage behavior. This indirect role refines prior extended TAM studies that predominantly model trust as a direct predictor of behavioral intention or usage.

Second, the study introduces individual impact as an outcome construct that captures realized cognitive and academic benefits rather than mere behavioral intention. While many TAM-based studies terminate at intention or use, this research empirically demonstrates that self-reported usage frequency translates into perceived personal and academic gains. By linking usage behavior to outcome-based benefits, the study bridges technology adoption literature with learning effectiveness research in higher education.

Third, instead of focusing on a single platform (e.g., ChatGPT), this research conceptualizes generative AI chatbots as a category of conversational learning technologies. The contribution therefore lies not in comparing platform-specific affordances, but in theorizing Gen-AI chatbots as a broader technological phenomenon characterized by conversational intelligence, generative content production, and adaptive epistemic support. This approach enhances the generalizability of TAM in rapidly evolving AI ecosystems, where students interact with multiple platforms interchangeably.

Together, these contributions strengthen the theoretical positioning of TAM within contemporary Gen-AI adoption research and provide a refined understanding of how trust and perceived cognitive value shape self-reported usage and individual-level outcomes in higher education.

Practical Implications

From a practical standpoint, the findings suggest that fostering the adoption of generative AI chatbots requires a coordinated effort between technology developers and educational institutions. To translate these theoretical constructs into actionable strategies, the following distinctions are made:

For Technology Developers (Design Levers):

- **Enhancing PEU & PU:** Developers should prioritize conversational UI/UX design that minimizes the learning curve (Davis, 1989). Features such as prompt suggestions, intuitive feedback loops, and multi-modal capabilities (voice-to-text, image recognition) can directly lower cognitive barriers (PEU). Furthermore, to boost PU, developers should focus on domain-specific fine-tuning, ensuring that chatbots provide high-quality, academically relevant, and accurate content that aligns with student needs.
- **Building Trust through Transparency:** Since trust acts as a perceptual scaffold, vendors must implement "transparency by design." This includes clear disclosure of data usage policies, the use of explainable AI (XAI) to show how answers are generated, and robust privacy features to mitigate concerns regarding academic surveillance (Wu et al., 2011).

For Educational Institutions and Educators (Institutional Actions):

- **Integrating PU into Pedagogy:** Universities should move beyond passive access and actively integrate chatbots into course design. Faculty can design assignments that require "human-AI collaboration," such as using AI for initial brainstorming or code debugging, thereby demonstrating the tool's utility in achieving specific learning goals.
- **Trust and Academic Integrity:** Institutions should establish clear ethical guidelines and "AI literacy" programs. By clarifying what constitutes "fair use" versus "academic dishonesty," universities can reduce the uncertainty and "fear of penalty" that might hinder students' trust in using these tools.
- **Maximizing Individual Impact:** To turn usage into tangible outcomes, institutions should provide support services like Prompt Engineering workshops. These actions ensure that engagement is not just frequent but "meaningful," leading to realized benefits in self-regulated learning and academic efficiency (DeLone & McLean, 2003; Chan & Hu, 2023).

Conclusion

This study provides important insights into the adoption of Gen-AI based chatbots in higher education, highlighting the roles of perceived ease of use, perceived usefulness, trust, and self-reported usage in shaping students' personal benefits. While the findings advance understanding of AI-based learning tools, several limitations should be considered, which also inform directions for future research.

First, the cross-sectional survey design limits the ability to draw causal conclusions. Longitudinal studies are recommended to examine how students' perceptions, usage behaviors, and learning outcomes evolve as chatbots become more integrated into curricula. Second, the study sample was drawn exclusively from one Turkish public university, which may constrain the generalizability of the results. In addition, the use of convenience sampling may have resulted in the overrepresentation of students who are more technologically inclined or familiar with AI-based tools, potentially biasing the findings toward more favorable perceptions of chatbot usage. Cross-cultural comparative studies could provide valuable insights into how cultural and institutional differences influence adoption patterns and educational outcomes. Third, reliance on self-reported data introduces potential biases, including social desirability and recall effects. In particular, usage was measured through students' self-reported frequency of chatbot usage rather than objective system log data. While this approach is consistent with a substantial body of survey-based TAM and IS research in which behavioral use is captured through perceptual measures, self-reported usage may be subject to overestimation or response bias, potentially affecting measurement precision and construct validity. Future research could complement survey-based measures with objective usage records or system log data to enhance robustness. Additionally, mixed-method approaches, such as interviews, focus groups,

or classroom observations, could provide more nuanced and contextually grounded insights into learners' experiences, expectations, and barriers to chatbot adoption.

In addition, while this study found that trust significantly influenced perceived ease of use and perceived usefulness, its direct effect on usage was not significant. This suggests that trust primarily operates through indirect pathways rather than as a direct behavioral driver. Subsequent studies might investigate the pathways of this indirect effect by considering factors like perceived risk, privacy issues, transparency of the system, and ethical aspects. Prior literature supports this perspective: for instance, Chong et al., (2023) demonstrated that trust affects usage intentions indirectly via cognitive perceptions like usefulness and attitudes, while other studies highlight that trust in technology providers enhances perceived usefulness and ease of use, which in turn drives actual system usage (Venkatesh et al., 2012; Wu et al., 2011). Longitudinal or mixed-method studies could also investigate moderating factors such as user experience, cultural context, or prior familiarity with AI tools, providing a more comprehensive model of trust-mediated usage in AI-based educational technologies.

From a practical standpoint, institutions and developers are encouraged to enhance the usability and perceived usefulness of AI-based tools while fostering trust through transparency, ethical guidelines, and clear communication regarding data privacy. Promoting meaningful engagement with Gen-AI based chatbots can maximize the personal and academic benefits for students, supporting both learning effectiveness and long-term adoption.

CRediT Authorship Contribution Statement

M. F. Gelibolu: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing – Original Draft, Writing - Reviewing & Editing, Visualization, Supervision.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Ethics Approval and Consent to Participate

This study was approved by the Ethical Commission of Gazi University (Approval No. E-77082166-604.01-1189515). The approval was granted on 12nd March 2025, and it covers all aspects of the research involving human participants.

Declaration of AI Usage Statement

In this study, the AI tools ChatGPT (access date: 03.03.2026; Version 5.3) and Gemini (access date: 03.03.2026; Version 3.1) were used. The tools were utilized for supportive purposes only, and the scope of use was to correct spelling errors and proofreading. All content generated or suggested by AI has been reviewed for accuracy and originality by the author, who takes full responsibility. Data obtained through AI tools was reviewed in accordance with ethical and academic principles. AI was used in compliance with COPE and Kastamonu Education Journal publication policies. AI has not been listed as an author or co-author. The scientific content, accuracy, originality, and ethical responsibility of the work belong entirely to the author.

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