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Motivational Drivers of Generative AI Continuance: An Integrated Uses and Gratifications and UTAUT2 Perspective

DERYA SAHIN

deryasahin2@aydin.edu.tr

Istanbul Aydın University

Article

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Abstract

This study examines the motivational factors shaping ısers' continuance intention toward generative artificial intelligence (GAI) by integrating the Uses and Gratifications theory (U&G) with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. Drawing on a cross-sectional survey of Gen Z users in Turkey (N=689), the research investigates how functional, social, and experiential motivations influence trust and continuance intention toward generative AI. Path analysis results reveal that task efficiency, performance expectancy, and trust are the strongest predictor of continuance intention. Conversely, hedonic motivation and social interaction negatively affect both trust and continue intention. Information seeking positively predicts continue intention but show no significant effect on trust. Overall, the findings underscore the primacy of utilitarian and performance-oriented motivations over hedonic and social drivers in fostering sustained generative AI use. This study contributes to the literature by offering an integrated, user-centered framework for understanding continue intention in the generative AI context.

1. Introduction

The recent diffusion of generative AI technologies has refocused interest in user interaction with such technologies and what drives users to adopt and continue to use them (Silalahi, 2024). Large language-based generative AI systems are no longer simply information or task-oriented platforms but are increasingly offering users personalized and human-interaction experiences (Jang et al. 2024). This serves to indicate how generative AI is no longer a strictly functional technology but is now a technology assessed from users' subjective experiences.

Existing research has extensively examined the application areas of generative AI, along with the opportunities it offers and the ethical, privacy related and trust-based risks it entails (Amos and Zhang, 2024; Wang and Yan, 2025; Peng and Li, 2025; Roberto et al. 2025). However, much of this literature either concentrates on technical performance or addresses user engagement in a relatively limited manner. In particular, studies (Baek and Kim, 2023; Huy et al. 2024; Kim et al. 2024) that systematically explore why users adopt generative AI, how their underlying motivations relate to trust and how trust shapes intention to continue using these systems remain scarce. The lack of an integrated perspective that connects user motivations, trust and continuance intention represents a notable gap in the current literature.

Within technology adoption research, the UTAUT2 model provides a robust frameworks explaining users' acceptance of new technologies (Arain et al. 2019). Nevertheless, this model primarily emphasizes (Long and Suomi, 2025) cognitive evaluations such as performance expectancy, perceived usefulness, and ease of use, while giving comparatively less attention to users' subjective needs and experience-based motivations. In this regard, U&G theory offers (Gao, 2023; Chen et al. 2025) a complementary perspective by emphasizing that individuals actively engage with technologies to satisfy specific needs and expectations. Despite this potential synergy, empirical studies integrating UTAUT2 with U&G approach in the context of generative AI remain limited.

The primary contribution of this study lies in addressing this gap by examining generative AI use through the interconnected lenses of user motivations, trust and continue intention. Drawing on an integrated framework

that combines U&G theory with the UTAUT2 model, the study investigates how motivational factors (Diaz et al. 2026) including information seeking, task efficiency, personalization, social interaction, performance expectancy, hedonic motivation and anthropomorphism shape users' trust in generative AI systems and their intention to continue them. By doing so, the study seeks to move beyond technology-centered explanation and instead highlight the role of user experience and perceptual processes in shaping generative AI adoption and sustained use.

Accordingly, the study addresses the following research questions:

RQ1: How do user motivations influence trust in generative AI systems?

RQ2: How do user motivations affect users' intention to continue using generative AI systems?

RG3: What role does trust play in the relationship between user motivation and continue intention?

From a theoretical perspective, this study contributes to the generative AI literature by offering a user-centered and integrative framework for understanding continue technology use. From a practical standpoint, it provides insights for developers and policymakers seeking to design more human-oriented generative AI that foster user trust and support sustainable engagement.

2. Theoretical Framework

2.1. Uses and gratifications theory (U&G)

U&G is a foundational theoretical framework within communication studies for explaining users' motives to use mass media (Severin and Tankard, 1992). U&G theory argues that media users are active participants who select media content. This theory highlights individuals' active and planned nature in choosing particular media technologies to satisfy their motives and desires (Katz et al. 1973). Numerous studies (Lim and Ting, 2012; Che et al. 2023; Nguyen and Nguyen, 2024; Qiao et al. 2024) based on this theory have found it valuable in exploring consumers' motivations for using different types of media. The U&G theory can serve as a theoretical framework to examine user motivations for using generative AI and how it addresses user needs. As noted by Yu (2024) individuals are driven to actively engage in the act of communication and engage with media to gratify their own needs and desires instead of being passive media users.

The U&G theory provides a significant framework to examine personal motivations and experiences with AI-driven technologies in diverse context (Chai and Wohn, 2019). That's why within the scope of human-AI interactions U&G theory can be employed (Gao, 2023) to better explain what motivates users engage with AI (Wu et al. 2025) and how AI can satisfy their particular needs. In fact, users tend to rely on AI to fulfil their cognitive needs by searching for information and solutions or they may use AI to satisfy their emotional needs (Kang and Lou, 2022) by interacting with a voice assistant or chatbot for emotional reassurance or enjoyment. The U&G has proven highly productive and has recently been employed to investigate consumers' adoption of artificial intelligence tools across different contexts. Several studies investigated the determinants that influence user gratification. For example, Baek and Kim (2023) investigated how various motivational drivers were associated with users' trust in generative AI along with perceived

crepiness which was subsequently linked to continuance intention. Moreover, Pitardi and Marriott (2021) analyzed how social, technological, hedonic, and utilitarian gratifications shape users' trust in Alexa on AI-powered voice assistant. Likewise, Lee and Cho (2020) identified four key motivations for engaging with AI smart speakers (information learning, practicability, virtual interaction, and relaxation). Similarly, Skjuve et al. (2024) found six key motivations for using ChatGBT: learning, productivity, novelty, entertainment, social interaction, and creative work illustrating the wide range of user motivations. Also Ju and Stewart (2024) identified entertainment, information seeking, social interaction, and efficiency as primary drivers of ChatGBT adoption. Gratifications affect future behavior as well. Intention to use conceptualized as the probability of engaging with a generative AI in the future is a stronger predictor of actual continued usage. Previous research have shown greater levels of gratification generally lead to stronger intention to use (Niu et al. 2024; Li et al. 2025; Liao, 2025).

As interaction frameworks between humans and machines progress, the U&G approach can help clarify why users are progressively more attracted to generative AI and how generative AI systems fulfil diverse user needs. Exploring these motives could support in developing human-centered AI models, boosting user satisfaction and trust toward technology (Puxiu et al. 2025). Building on U&G theory as a user focused framework this study examine varied uses of AI among consumers and their motivation with generative AI.

2.2. UTAUT2 Model

The researcher is consistently concerned with examining how people embrace and use technological progress within information and communication technologies (Cabrera-Sánchez et al. 2021; Uludağ et al. 2025). UTAUT developed by Venkatesh et al. (2003) represents a highly influential framework for forecasting user adoption of innovative technologies. UTAUT highlights four primary determinants (performance expectancy, social influence, effort expectancy, and facilitating condition) to forecast users' behavioral intention regarding a technological system or innovation. Despite its strengths, it presents some limitations when applied across diverse technological contexts. To strengthen the explanatory capacity of UTAUT within consumer context, Venkatesh et al. (2012) developed UTAUT2 including hedonic motivation, habit and price value as new explanatory variables.

UTAUT2 was not developed to have a singular emphasis on but instead to function as a comprehensive framework for examining technology adoption (Marikyan and Papagiannidis, 2021). That's why this extended model notably enhances forecasting ability predicting user's behavioral intention. Both UTAUT and its extended version, UTAUT2 have been extensively employed to investigate the adoption of AI-based systems. Empirical studies have applied UTAUT2 model to understand behavioral intention toward generative AI (Yin et al. 2023; Cabero-Almenara et al. 2024; Grassini et al. 2024; Ke et al. 2025). For example, Gulati et al. (2024) investigation of students demonstrated that habit was the strongest determinant affecting behavioral intention. Similarly, Xu et al. (2024) demonstrated that several predictors related to behavioral intention to use generative AI including performance expectancy and hedonic motivation.

2.3. Hypothesis Development

2.3.1. Information seeking

Information seeking refers to individuals utilizing information technologies to look for information addressing to their needs. It involves various processes such as examine, recognize, express, acknowledge, reframe, and use (Marchionini and White, 2007). Previous research has investigated information seeking in generative AI. For example, Skjuve et al. (2023) highlighted that generative AI user experience is affected by both utilitarian and hedonic motivation. Similarly, Wang et al., (2025) revealed that functional factors such as information seeking and performance had a direct effect on behavioral intention. To explore the conceptual validity of this connection, a hypothesis is forwarded below.

H1: Information seeking positively affects trust in generative AI

H2: Information seeking positively affects continuance intention in generative AI

2.3.2. Task Efficiency

Task efficiency refers to the degree to which a technology allows users to accomplish tasks in an easier and faster, and more efficient way by reducing time and effort. In the context of AI-based technologies, task efficiency captures users' perceptions that the system facilitates goal-oriented. Previous studies have validated the connection between task efficiency and continuance to use via trust. (Baek and Kim, 2023; Huy et al. 2024). To ascertain the effects of task efficiency associated with generative AI, trust, and continuance intention in generative AI, the following hypotheses are proposed.

H3: Task Efficiency positively affects trust in generative AI

H4: Task Efficiency positively affects continuance intention in generative AI

2.3.3. Personalization

Personalization in a generative AI system context refers to utilizing user experience to customize and modify the produced responses, offering information and suggestions based on the user's needs, preferences, and conventional behaviors (Baek and Morimoto, 2021). Recent studies have shown that personalization in generative AI plays a important role to shaping user experience. Valz (2023) demonstrated that generative AI systems can adopt themselves based on user feedback and users's needs. Teeny and Matz (2024) revealed that personalization needs to be perceptible to users in order to meaningfully address their individual needs and interests.

To explore the conceptual validity of this connection, a hypothesis is forwarded below.

H5: Personalization positively affects trust in generative AI

H6: Personalization positively affects continuance intention in generative AI

2.3.4. Social interaction

Social interaction refers to a crucial social motivation that reflects individuals' need to communicate with others, share thoughts and emotions, receive feedback, and engage in reciprocal exchanges. Within the U&G framework, social interaction refers to individiuals' motivation to engage in communication, companionship,

and relational exchange through media technologies (Whiting and Williams, 2013). While generative AI systems increasingly adopt conversational and socially oriented interactions may not always foster positive user outcomes (Liu and Sundar, 2018; Hu and Lu, 2021; Leib et al. 2025). Because in the context of generative AI, users who seek social interaction may experience discomfort when interacting with generative AI. Extant research assessing the role of social interaction in generative AI, has generated inconsistent findings. For instance, Makkonen et al. (2023) revealed social interaction has negatively affects to trust in generative AI. Baek and Kim (2023) demonstrated social interaction as an important predictor of generative AI. To test the individual effect of social interaction on trust and continuance intention we advance the following hypotheses.

H7: Social interaction negatively affects trust in generative AI

H8: Social interaction negatively affects continuance intention in generative AI

2.3.5. Performance Expectancy

The performance expectancy construct clarifies how employing technology can advantage users when performing specific tasks (Venkatesh et al. 2012). People are more likely to use a technology if they are persuaded it will support their performance (Sewandono et al. 2023). Several studies have shown that performance expectancy has a significant effect on trust and intention to use in generative AI (Jain et al. 2022; Kavitha and Joshith, 2024; Huy et al., 2024). To explore the conceptual validity of this connection, a hypothesis is forwarded below.

H9: Performance expectancy positively affects trust in GAI

H10: Performance expectancy positively affects continuance intention in GAI

2.3.6. Hedonic motivation

Hedonic motivation indicates the extent to which people are driven to use a particular technology for the inherent pleasure, enjoyment, or novelty it offers (Venkatesh et al. 2012; Le at al. 2024). People carry out specific activities to experience the enjoyment and pleasure inherent in these activities (Kim et al. 2025). Previous studies have shown (Pramod et al. 2024; Bak et al. 2025; Feng et al. 2025) that hedonic motivation has a significant impact on generative AI. However, the influence of hedonic motivation on users' evaluations of generative AI systems might vary across cultural context. Research conduct in Turkey indicates that (Kirgiz, 2014; Sütütemiz and Saygılı, 2020; Güçlü et al. 2023) hedonic consumption tendencies are closely associated with expectation of emotional gratification and pleasure; however such expectations may not always be fully met by generative AI systems that are primarily designed around functional and instrumental use logic. To explore the conceptual validity of this connection, a hypothesis is forwarded below.

H11: Hedonic motivation negatively affects trust in generative AI

H12: Hedonic motivation negatively affects continuance intention in generative AI

2.3.7. Anthropomorphism

Anthropomorphism is define as attributing human-related features, emotions, or characteristics to artificial agents (Epley et al. 2007). The communication and human-computer interaction literature shows that when technological systems display human-like cues, perceive them as more social, relatable, and open to interaction (Epley, 2018). In the context of generative AI, anthropomorphism is strengthened by these systems' ability to use natural language, produce coherent responses, and sustain interaction. Recent studies have shown that generative AI tools based on large language models display human-like communication patterns, which increase users' tendency to engage in social interaction and lead them to perceive these systems as social counterparts (Blut et al. 2021; Troshani et al. 2021; Qiao et al. 2024). To test this theoretical assumption, a hypothesis is postulated below.

H13: Anthropomorphism positively affects trust in generative AI

2.3.8. Trust

Trust is conceptualized as the level to which individuals perceive the information or suggestions provided by technology as trustworthy and believable. Trust is a fundamental determinant of usage behavior and has been broadly applied as a significant indicator of usage intentions research on technology adoption. Empirical studies have demonstrated (Dunn et al. 2023; Amoozadeh et al. 2024; Piller et al. 2024; Yuan et al. 2024) that trust in AI can have beneficial outcomes, including perceived effectiveness of AI and purchase intention. To explore the conceptual validity of this connection, a hypothesis is forwarded below.

H14: Trust positively affects continuance intention in generative AI

3. Proposed Conceptual Model

To illustrate the interrelationships between the theoretical constructs and the research hypotheses, a conceptual model is shown below (Figure 1).

4. Method

We conducted a cross-sectional survey with Gen Z college students in Turkey. As discussed above, Gen Z is a desired consumer target due to the fact that they are the first generation to grow up with the introduction of generative AI. According to a recent global consumers study by Google in collaboration with Kantar, about 84 % of the Gen Z consumers expressed a strong desire to use generative AI (Google and Kantar, 2024, as reported in the Economic Times).

Participant recruitment, followed by online data collection, commenced with prior ethical approval (Istanbul Aydin University, approval number:2025/12). Prior to participation, all participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without penalty. Informed consent was obtained from all participants in written form via the online survey. After data cleaning, the study yielded 689 valid cases. The sample's gender split included 69.1% females and 30.9% males. Unless otherwise noted, the measurement scale adopted for assessing all the variables

was a five-point Likert-type scale (1 = Strongly Disagree and 5 = Strongly Agree). A principal component factor analysis was conducted to generate the conceptual clusters for each variable. Each of these conceptual cluster was tested validated for their inter-item reliability with a Cronbach's alpha test.

Information seeking was measured using 3 items adapted from the "information seeking" scale by Baek and Kim (2023). Sample items include: "*I use generative AI because I can seek information to satisfy my curiosity*," and "*I use generative AI because I can seek information to enhance my knowledge and skills*." (α=0.86). Task efficiency was assessed by 4 items adapted from Choi and Drumwright (2021) study. Example items are: "*I use generative AI because it saves time completing my task.*" and "*I use generative AI because it makes my task easier*." (α=0.88). Personalization was evaluated by 4 items adapted from Baek and Kim's study (2023). Selected items are as follow: "*I use generative AI because using generative AI is customized to my needs*" and "*I use generative AI because using generative AI is tailored to my unique specifications*" (α=0.81). Social interaction was evaluated by 4 items adapted from Choi and Drumwright's study (2021). Sample items include: "*I use generative AI because it is always there for me when I want to talk*." and "*I use generative AI because I can have a conversation when I feel sad"* (α=0.87). Hedonic motivation was evaluated by 4 items adapted Venkatesh et al (2012)'s study. These items include: "*Using generative AI is fun.*" and "*Using generative AI is enjoyable*." (α=0.87). Performance expectancy was evaluated by 4 items adapted Venkatesh et al (2012)'s study. Selective items include: "*I find generative AI useful in my daily life*." and "*Using generative AI helps me accomplish things more quickly"* (α=0.88). Trust was evaluated by 4 items adapted from Afshan and Sharif' study (2016). Sample items include: *"Generative AI seems dependable*" and "*Generative AI seems reliable*" (α=0.87). Anthropomorphism was measured using 3 items adapted from the "anthropomorphism" scale by Kim et al. (2023). Example items are: "*Generative AI can engage in human-like conversations*." and "*Generative AI provides a sense of intimacy similar to that of humans*." (α=0.77). Continuance intention was evaluated by 2 items Choi and Drumwright's study (2021). Selected items are as follow: "*I plan to keep using generative AI*" and "*I want to continue using generative AI*" (α=0.93).

5. Result

Table 1 presents the descriptive statistics for all constructs. The results show that the cluster of variables garnered the highest mean belonged to the functional factors. Specifically, information seeking and continuance intention yielded the highest mean value, followed by task efficiency, performance expectancy, and hedonic motivation. Social interaction, trust, and anthropomorphism resulted with middling-level means.

Table 1 Descriptive statistics for key variables

Variables	M	SD	N
Information Seeking	3.74	1.20	689
Task Efficiency	3.66	1.15	689
Social Interaction	3.15	1.24	689
Personalization	3.31	1.08	689
Performance Expectancy	3.56	1.15	689
Hedonic Motivation	3.36	1.12	689
Trust	3.26	1.06	689
Anthropomorphism	3.05	1.12	689
Continuance Intention	3.74	1.32	689

The correlations results reported in Table 2 indicate that all the variables were significantly correlated with each other. Specifically, continuance intention had strong connection with task efficiency, performance expectancy, and trust. Overall, result show that more rational and utilitarian variables tend to have stronger relationships, highlighting the importance of functional considerations.

Table 2 Correlations between key variables

	1	2	3	4	5	6	7	8
1 Information Seeking	--							
2 Task Efficiency	0.59**	--						
3 Social Interaction	0.10**	0.16**	--	--				
4 Personalization	0.41**	0. 44**	0.27**					
5 Performance Expectancy	0.48**	0.57**	0.20**	0.33**	--			
6 Hedonic Motivation	0.32**	0.37**	0.42**	0.34**	0.28**	--		
7 Trust	0.35**	0.41**	0.05**	0.37**	0.41**	0.18**	--	
8 Anthropomorphism	0.14**	0.16**	0.28**	0.28**	0.23**	0.30**	0.30**	--
9 Continuance Intention	0.67**	0.64**	-0.01**	0.35**	0.66**	0.17**	0.53**	0.18**

Note: * p < 0.05; **p < 0.01 (2-tailed)

A path analysis procedure was utilized to test all the research hypotheses. The results revealed a good model fit, $\chi 2/df=2.33$, p< 0.001, CFI=0.95, NFI=0.92, IFI= 0.95, TLI= 0.95, RMSEA= 0.044. The path modeling result indicated that information seeking was a non-significant predictor of trust; H1 (β=0.04, p =.0.484). Turning to H2, which was supported by the results showing a positive relationship between information seeking and continuance intention (β=0 .40, p <0.001). The same is true for both H3 and H4, as results indicated that while perceived task efficiency was significantly predicted trust (β=0.17, p =.0.008), it was also a significant predictor of continuance intention (β=0 .20, p <0.001) as well. H5 was confirmed, as perceived personalization positively predicted trust (β=0 .22, p <0.001). However, H6 was not confirmed by the results because personalization was a non-significant predictor of continuance intention (β= -0 .022, p =.0.514).

The path analysis results supported both H7 and H8. In particular, social interaction was significant predictors of trust (β= -0 .14, p =.0.001) and continuance intention (β= -0 .13, p <0.001). The same is true for both H9 and H10, as results indicated that while performance expectancy was significantly predicted trust (β=0 .23, p <0.001), it was also a significant predictor of continuance intention (β=0.33, p< 0.001). (β=0 .35, p <0.001). H11 was not confirmed by the results because hedonic motivation was a non-significant predictor of trust (β= -0 .070, p =.0.162). The opposite is true for H12, as a positive relationship was found between hedonic motivation and continuance intention (β= -0 .14, p <0.001). H13 was also confirmed, as perceived anthoropomorphism positively predicted trust (β= 0 .26, p <0.001). Lastly, H4c were validated by the results, as respectively had a positive relationship between trust and continuance intention (β= .18, p <0.001).

Table 3 Structural path relationships

H	Structural Path	Stan. (β)	P-value	Result
H1	Information seeking→ Trust	0.04	0.48	Not supported (p >.05)
H2	Information Seeking→ Continuance intention	0.40	***	Supported
H3	Task Efficiency→ Trust	0.17	0.00	Supported
H4	Task Efficiency→ Continuance intention	0.20	***	Supported
H5	Personalization→ Trust	0.22	***	Supported
H6	Personalization→ Continuance intention	-0.02	0.51	Not supported (p >.05)
H7	Social interaction→ Trust	-0.14	0.00	Supported
H8	Social interaction→ Continuance intention	-0.13	***	Supported
H9	Performance expectancy→ Trust	0.23	***	Supported
H10	Performance expectancy→ Continuance intention	0.35	***	Supported
H11	Hedonic motivation→ Trust	-0.07	0.16	Not Supported (p >.05)
H12	Hedonic motivation→ Continuance intention	-0.14	***	Supported
H13	Anthropomorphism→ Trust	0.26	***	Supported
H14	Trust →Continuance intention	0.18	***	Supported

6. Discussion

The current study proposed and tested a conceptual model that integrated two bodies of theoretical literature to examine consumers' generative AI intention decision-making process. In particular, the study design starts with the assumption that consumers' intention to continue using generative AI are shaped by both goal-oriented motivations and technology-related performance evaluations. Specifically, motivational factors derived from (Florenthal, 2019) U&G such as, information seeking, task efficiency, and social interaction. Similarly, UATAUT2-based constructs (Cabero-Almenara et al. 2024) particularly hedonic motivation and performance expectancy, reflect consumers' assess of generative AI's usefulness and experiential values. We also explore the moderating role of trust in the relationships between multiple influencing factors on generative AI continuance intention.

Our study results supported the conceptual model by validating all but three of the fifteen research hypotheses. The three research hypotheses that were non-significant tested the relationship between information seeking and trust (H1), personalization and continuance intention (H6) as well as between hedonic motivation and trust (H11). The results showed that dimensions of UTAUT2 and trust played a significant role in explaining continuance intention toward generative AI. Overall, these results are consist with most previous studies (Yin et al. 2023; Grassini et al. 2024; Tang et al. 2025) on generative AI use with respect to performance expectancy, however, they do not concur with most prior findings (Maican et al. 2023; Hu et al. 2025; Segeeva et al. 2025) regarding hedonic motivation. Users who convince generative AI as effective and useful for accomplishing tasks are more likely to trust generative AI systems and continue using them (Thorne, 2024). Contrary, the result demonstrated that hedonic motivation played a relatively minor role through using generative AI. While hedonic motivation negatively affected continuance intention, it did not have a significant effect on trust. This result indicates that novelty and enjoyment may not promote continuance intention and are not sufficient to build trust in generative AI. Trust seems to be primarily driven by utilitarian value and performance assessments rather than on hedonic experiences.

When examined through the Uses and Gratifications framework, the findings provide deeper insight into the role of particular motivational drivers in generative AI use. Our study revealed that information seeking has a significant positive effect on continuance intention but did not significantly influence trust. That's why our findings suggest that when users rely on generative AI to fulfil knowledge-related and informational needs, it may support continuance intention. Remarkably, we found that task efficiency played a more central role in trust and continuance intention. Users who consider generative AI as time-saving and minimize required effort are more likely to trust generative AI systems and continue using it. Compared to information seeking, task efficiency indicates a more comprehensive assessment of system utility, which can help explain its more robust relationship with trust.

We also found that personalization had a positive association with trust but did not significantly affect continuance intention. A plausible explanation for why personalization did not significantly affect continuance intention could be that personalization by itself may be insufficient if users fail to perceive adequate functional benefits. Researchers and practitioners alike should consider new or enhanced methodological approaches to better understand how generative AI usage motivations may interact with the personalization factor in generative AI users' decision-making processes. Finally, we found that social

interaction had a negative effect on both trust and continuance intention. These findings suggest that socially oriented interactions with generative AI may evoke unease rather than user engagement. This may be explained by users' evaluations of interactions with AI as intrusive instead of supportive.

7. Theoretical implications

This study provides several conceptual implications for research on users' continuance intention of generative AI. First, it introduced a combined model that provides a comprehensive explanation of generative AI continuance intention by integrating the Uses and Gratifications theory and UTAUT2. We extended the model by integrating trust as a moderator to investigate generative AI continuance intention. The proposed integrated framework addresses the constraints of single-theory frameworks and allows a comprehensive understanding of continuance intention for generative AI.

Second, the role of trust should be considered in light of the specific features of generative AI systems such as their relatively recent emergence (Huy et al. 2023) open accessibility (Basyoni et al. 2025; Li et al. 2025) and inconsistent (Almagrabi et al. 2024; Nguyen-Duc et al. 2025) credibility of AI-generated context. Accordingly, the proposed framework goes beyond single-theory explanations and allows a more refined and context-sensitive understanding of continuance intention within generative AI context.

Third, this study highlights the contextual relevance of the proposed frameworks by investigating these relationships within the Turkish Gen Z context (Yilmaz et al. 2024; Alagöz Hamzaj, 2025; Ozkan and Kaygısız, 2025), providing insights relevant to similar cultural and generational settings. These insights suggest that generative AI systems focusing on younger user segments should be developed and presented with particular emphasis on utilitarian value, task efficiency, and performance-related benefits.

8. Practical implications

The findings of this study provide significant implications regarding the marketing communication of generative AI systems such as ChatGPT, Gemini, and Claude. The results indicate that users' trust is primarily influenced by perceptions of performance expectancy and task efficiency (Choudhury and Shamszare, 2024; Huy et al. 2024). Therefore, marketing communication messages should highlight how generative AI systems support task completion decrease time and effort, and offer measurable performance-related benefits. These function-focused and benefit-oriented communication strategies may strengthen user trust as well as foster continuance intention in the long time.

Moreover, our results suggest that may not be sufficiently motivated to demonstrate continuance intention toward generative AI systems for purposes associated with hedonic motivation and social interaction. Thus instead of highlighting socially expressive and the entertainment features of generative AI practitioners should emphasis the functional advantages of these technologies such as task-related support and efficient task completion. Our findings also point to the significance of developing trust with generative AI users.

These approaches are anticipated not only to extend the user population but also to support sustain growth and long-term development. By aligning systems design and communication strategies with users'

functional expectations and concerns related to trust system providers can support deeper and more enduring user relationship. In the long term this strategy may improve user satisfaction, strengthen loyalty, and contribute to responsible and scalable integration of generative AI technologies throughout varied application domains.

9. Limitation

This research has several limitations. First, even though utilizing a Gen-Z sample was a good choice for exploring future generative AI usage motivation, studying the general Gen Z instead of the college student population will make the findings more generalizable. Second, the current study documents generative AI diffusion at a single point in time. A more reliable approach would require a longitudinal study to generate comparable empirical evidence over time. Third, our conceptual model provided valuable preliminary findings to explain a complex phenomenon that involves multiple theoretical traditions. This conceptual model will need additional empirical efforts to confirm or improve its measurement reliability and validity. Furthermore, as the generative AI technology is still evolving, future studies should incorporate system intelligence features of generative AI to more effectively evaluate the need for the innovativeness construct.

Declarations

Ethical Approval

Ethical approval for this study was obtained from the Istanbul Aydın University Social and Human Sciences Ethics Committee (Meeting No: 2025/12) on 13 November 2025. The study was approved prior to the commencement of data collection. Data collection began on 14 November 2025 and was completed within one month. All procedures involving human participants were conducted in accordance with relevant ethical guidelines and regulations, including the principles of the Declaration of Helsinki.

Informed Consent

Informed consent was obtained online through a digital consent form presented at the beginning of the Google Forms survey. Participants were required to read the consent information and actively indicate their agreement before proceeding to the questionnaire. Participation was voluntary, and respondents were informed about the purpose of the study, confidentiality of their responses, and their right to withdraw at any time without penalty. All participants were 18 years of age or older.

Data Availability

The raw dataset underlying this study is publicly available in the Zenodo repository at: https://doi.org/10.5281/zenodo.18104371 The dataset contains fully anonymized participant data and does not include any personally identifiable information.

Author Contributions

Derya SAHIN: Conceptualization, methodology, survey design, data collection, formal analysis, writing—original draft, writing—review and editing.

Competing Interests

The author declares no competing interests.

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Figures

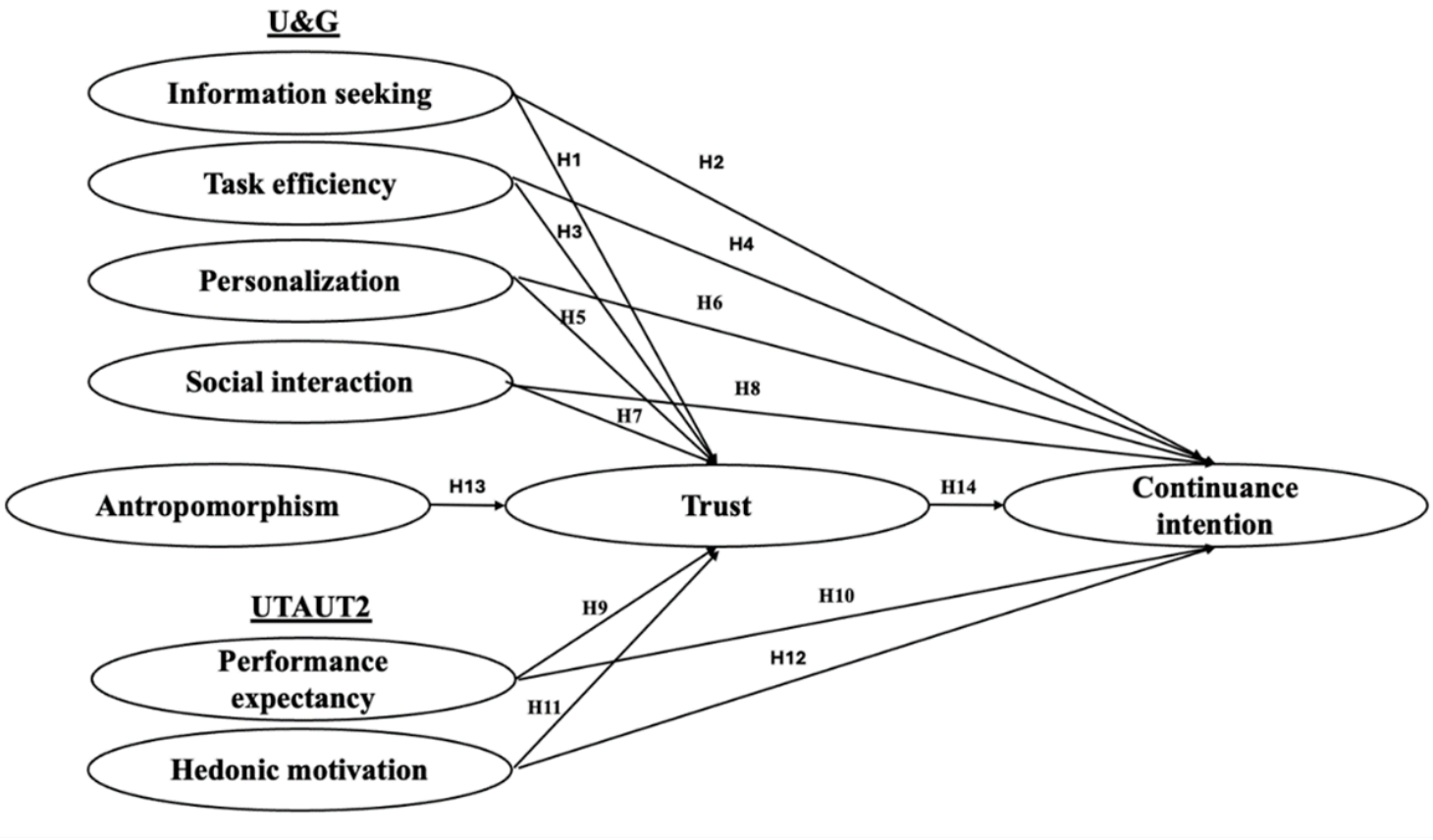


Figure 1

Proposed model