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Understanding Generative AI Continuance Intention: A Dual-Factor Perspective on Facilitators and Barriers

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Abstract

Purpose: This study aims to identify and explain the key factors that encourage or discourage users from continuing to use Generative Artificial Intelligence (AI) platforms. Specifically, the research examines how system-related facilitators (such as *interaction quality, personalization, reliability, and affordances*) and psychological barriers (including *inertia, perceived threat, and regret avoidance*) shape users' post-adoption attitudes and continuance intentions toward Generative AI.

Methodology: The survey data were collected from the respondents applying the purposive sampling technique. Structural equation modeling (PLS-SEM) was used in the analysis.

Findings: The study's results reveal that perceptions of interaction quality, personalization, reliability, creative affordance, and analysis affordance significantly promote the intention to continue using. Conversely, perceptions of inertia, threats, and regret avoidance significantly hinder continued use.

Limitations: The findings might not be widely generalizable. The data were collected only in a particular community.

Practical Implications: These insights offer critical implications for business owners, platform developers, and policymakers aiming to retain consumers of Generative AI products.

Value: To attain the objective, this research integrated the "Elaboration Likelihood Model" and "Status Quo Bias theory". It developed a conceptual model to address cognitive, emotional, and behavioral components.

Key Words: Generative artificial intelligence (AI), Generative AI, Continuance intention to use, AI-Human interaction, Technology adoption, AI research.

1. Introduction

Generative artificial intelligence (AI) has brought about a groundbreaking paradigm shift for humanity. It can produce diverse material and furnish individuals with more precise and dependable responses, mitigating the information overload people encounter. Generative AI tools developed by companies such as OpenAI (ChatGPT), Google (Gemini), Perplexity AI, and Anthropic (Claude) are now extensively used across a wide range of sectors. (Zhou and Ma, 2025; Khan *et al.,* 2025).

Although prior studies have examined generative AI continuance, the existing research remains predominantly enabler-driven and theoretically fragmented, offering limited insight into why users discontinue despite initial adoption. Most studies rely on single-theory models such as TAM, ISSM, and ECM. They focus on positive drivers, for instance, information quality, content quality (Zhou and Ma, 2025), perceived usefulness, perceived anthropomorphism (Kim *et al.,* 2024), effort expectancy, ethical considerations, expectation confirmation, and satisfaction (Baig and Yadegaridehkordi, 2025). It largely overlooks inhibitors such as inertia, perceived threats, and regret avoidance, which are especially influential in the highly personalized and emotionally sensitive context of generative AI (Shahzad *et al*., 2025). This gap highlights the need for an integrated dual-factor perspective that simultaneously captures facilitators and barriers shaping users' continued engagement. Motivated by this limitation, the present study contributes to the literature by developing and empirically validating a holistic model that integrates the "Elaboration Likelihood Model" and "Status Quo Bias" theory, providing a comprehensive explanation of the cognitive, affective, and bias-driven mechanisms that influence continuance intention. Additionally, by examining these dynamics in non-Western, emerging markets, this research enhances the generalizability of generative AI continuance theories. It offers practical insights for platform developers and policymakers seeking to reduce dropout rates and strengthen long-term user engagement (Khan *et al.,* 2025). Generative AI experiences are personal and highly subjective. Barriers may significantly outweigh perceived benefits in user decisions regarding continued engagement. Therefore, this research adopted an integrated theoretical perspective that simultaneously considers facilitator and barrier perspectives. This method offers more nuanced and comprehensive insight into consumer use of Generative AI.

This study's central objective is twofold:

(i) To systematically investigate and empirically examine the key facilitators and barriers shaping user attitude and influencing their persistent use intention for Generative AI.

(ii) To explain these insights into actionable guidance for enterprise owners, practitioners, and policymakers to enhance platform adoption, sustained user engagement, and overall effectiveness.

By advancing an integrated theoretical and empirical perspective, this study addresses a critical research gap and offers practical implications for optimizing Generative AI technologies. Ultimately, this research contributes significantly to the broader objective of leveraging Generative AI solutions to enhance their value and access for diverse populations.

2. Background Literature

Continuance engagement denotes an individual's constant intention to use an information system following initial adoption (Bhattacherjee, 2001; Khan *et al.,* 2025). It is an essential element in online retail marketing, since the costs of acquiring new customers are usually much higher than those of retaining existing ones (Khan and Furuoka, 2025). However, previous research demonstrated that user dropout rates on Generative AI are high, especially after initial adoption. This observation reveals a critical gap between first-time use and ongoing engagement, which is vital for the sustained growth and success of Generative AI.

Existing research on Generative AI adoption and continuance has concentrated on enablers that drive user acceptance, drawing on widely applied theoretical frameworks such as the *Technology Adoption Model", the "Information Systems Success Model", the "Expectation Confirmation Model", the "UTAUT2" and the "Uses and Gratifications Theory"* (Kim *et al.,* 2024; Zhou and Ma, 2025; Baig and Yadegaridehkordi, 2025). Prior research has examined post-adoption behavior from an enabling standpoint. It focused on motivational factors such as information and content quality (Zhou and Ma, 2025), perceived usefulness, and anthropomorphism (Kim *et al.,* 2024), effort expectancy, ethical considerations, expectation confirmation, and satisfaction (Baig and Yadegaridehkordi, 2025). These studies consistently underscore how such factors foster users' continued engagement with Generative AI platforms.

In contrast, relatively little research has examined barriers to the continuance of Generative AI. It highlights factors such as distrust and perceived loss (Shahzad *et al.,* 2025) as barriers to sustained usage. This research remains conceptually fragmented because it has rarely integrated structured theoretical lenses, such as "*Status Quo Bias,"* that can systematically capture the complexity of inhibitors (Samuelson and Zeckhauser,1988).

The simultaneous examination of enablers and inhibitors remains underexplored, leaving an incomplete understanding of the opposing forces that influence user continuance decisions in real-world Generative AI. Addressing this gap requires developing integrated models of facilitators and barriers which offers a holistic understanding of Generative AI continuance dynamics.

2.1. Theoretical Background: *Elaboration Likelihood Model as Facilitators*

The Elaboration Likelihood Model (ELM), introduced by Petty and Cacioppo (1981), is a dual-process theory that explains how individuals form and change attitudes through communication. According to ELM, persuasion occurs through two complementary routes: the central route, which involves effortful cognitive processing of message-related information, and the peripheral route, which relies on heuristic cues requiring minimal cognitive effort.

Within the ELM framework, argument quality and source credibility are recognized as core determinants of persuasive outcomes. Argument quality reflects the perceived strength, relevance, and usefulness of information provided, thereby influencing users' attitudes through central-route processing. Source credibility, typically conceptualized in terms of expertise and trustworthiness, serves as a peripheral cue that affects persuasion when individuals rely on heuristic evaluations. Prior research has consistently validated the importance of these constructs in digital contexts, including online platforms, chatbot-mediated interactions, and trust formation in technology-enabled environments.

In the context of Generative AI, however, persuasive influence extends beyond static message characteristics to encompass system-level interaction experiences. Accordingly, this study conceptualizes perceived interaction quality and reliability as technology-specific manifestations of argument quality and source credibility. High-quality interactions, with relevance, coherence, and responsiveness of AI-generated outputs, enhance users' cognitive evaluations of information, fulfilling the role of argument quality on the central route.

Similarly, perceived reliability reflects users' confidence in the consistency, accuracy, and dependability of AI-generated responses, capturing the credibility of the AI system as an information source.

This study extends ELM by incorporating perceptions of personalization, creative affordance, and analytical affordance as salient peripheral cues in Generative AI use. These experiential system features signal adaptability, creativity, and problem-solving capability, shaping user affective responses and reinforcing favorable attitudes with relatively lower cognitive effort. In post-adoption contexts, such cues become particularly influential, sustaining engagement and continued use.

By explicitly integrating argument quality and source credibility within a Generative AI-specific operationalization of ELM, this study advances the model's applicability. The revised framework demonstrates how cognitive evaluations and experiential system features jointly facilitate users' continuance intention toward Generative AI platforms.

2.2. Theoretical Background: *Status Quo Bias Theory (SQB) as Barriers*

This research contributed to AI research by incorporating the barrier perspectives (Status Quo Bias theory) that users consider when deciding about their continuance usage intention toward Generative AI. SQB theory, initially proposed by Samuelson and Zeckhauser (1988), comprises three primary constructs: psychological commitment (emotional loyalty to existing systems), cognitive misperception (biased judgments regarding alternatives), and rational decision-making (cost-benefit analyses that favor the status quo).

Fundamentally, this SQB theory explains individuals' tendency to favor maintaining existing conditions over adopting changes (Nel and Boshoff, 2020). It also offers valuable theoretical insights for understanding how attachment to incumbent systems can hinder the acceptance and adoption of new information technologies (Hsieh, 2015). Drawing from psychological theories, SQB has been widely applied in decision-making (Balakrishnan *et al.,* 2021). These studies justify the applicability of the SQB theory in technology adoption and continuance.

In applying SQB theory to Generative AI, this study identified perceptions of inertia, threats, and regret avoidance as key barriers. These inhibitor factors significantly prevent users from continuing to use Generative AI. Therefore, this research integrated these constructs into the conceptual framework to address the status quo bias in enhancing users' long-term engagement.

3. Conceptual Framework And Hypothesis Development

Figures 1 and 2 illustrate the proposed conceptual framework and graphical output.

Figure 1: Conceptual Framework

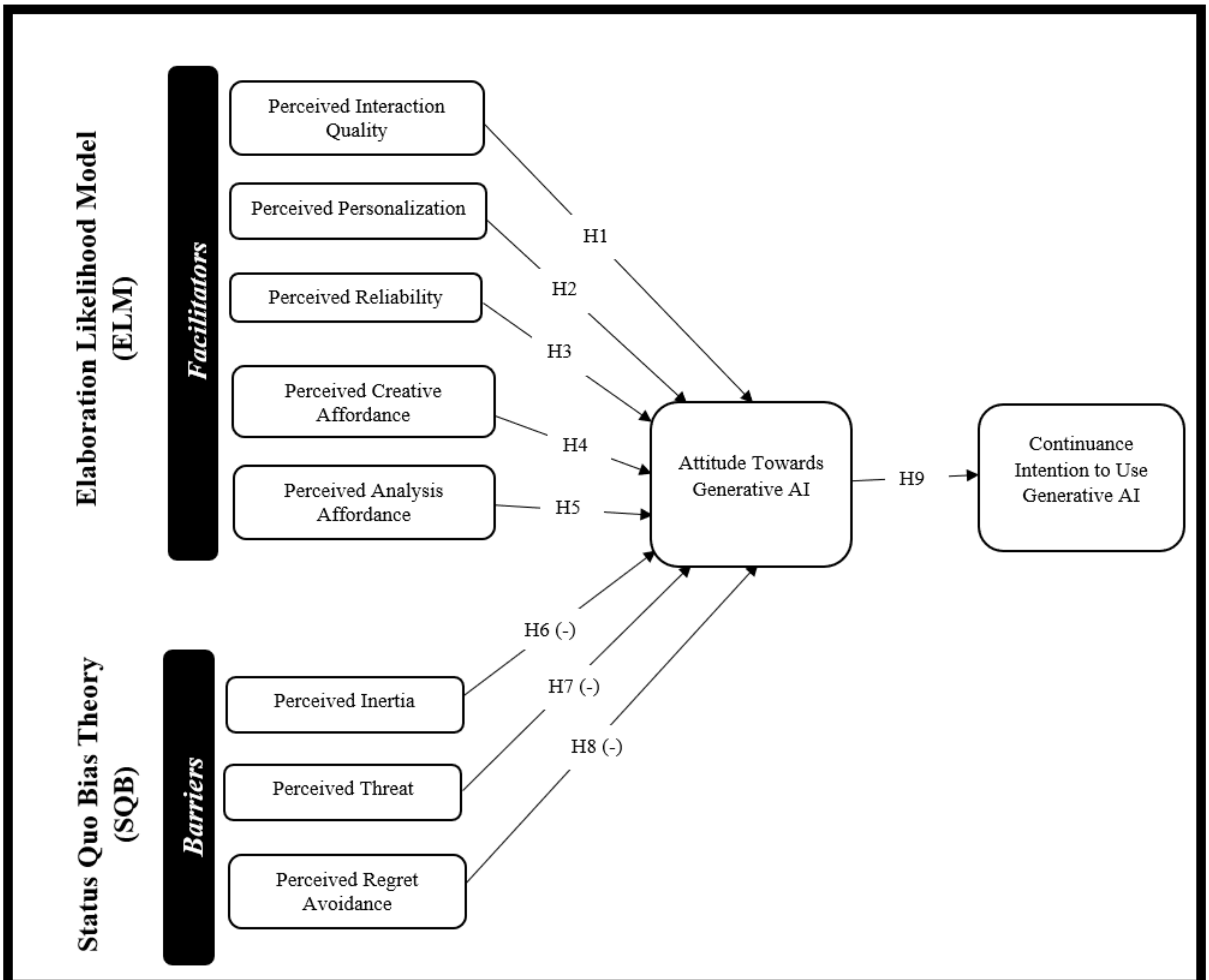

Figure 1: Conceptual Framework

Facilitators:

Perceived Interaction Quality and Attitudes:

The perceived interaction quality of Generative AI can be defined as the platform’s ability to facilitate two-way communication, including prompt responses and a convenient user interface (Zhou and Ma, 2025). Sun *et al.* (2026) emphasized that interactivity enhances consumer value and satisfaction, while Zhang *et al.* (2020) found it to be a significant determinant of user experience in mobile social networking environments. Improved interactivity through features, such as real-time chat, personalized recommendations, and responsive customer support, can boost user engagement, platform stickiness, and repeat usage (Sun *et al.,* 2026). Therefore, we hypothesize:

H1: Perceived interaction quality has a positive impact on attitudes towards Generative AI.

Perceived Personalization and Attitudes:

Perceived personalization refers to the degree to which technology, like Generative AI, tailors content to align with an individual user's preferences and needs (Zhou and Ma, 2025). This customization enables users to exercise autonomous choices, fostering a heightened sense of empowerment and a positive attitude (Balakrishnan *et al.,* 2021). Prior research has emphasized that personalized services have an important role in strengthening the users’ sense of empowerment and overall satisfaction (Wang *et al.,* 2026). Hence, we hypothesize:

H2: Perceived personalization has a positive impact on attitude towards Generative AI.

Perceived Reliability and Attitudes:

Perceived reliability refers to the extent to which users consider the information provided by Generative AI accurate, truthful, and trustworthy (Zhou and Ma, 2025). When users perceive that platform content is credible, their sense of uncertainty and perceived risk diminishes, making them more comfortable in relying on such content for decision-making (Zhou and Ma, 2025). Furthermore, perceived credibility helps mitigate users’ concerns regarding the so-called "information illusion" often associated with online platforms, fostering trust and encouraging continued usage (Gmiterek and Kotuła, 2025). Prior studies have underscored the influence of credibility on user behavior. Thus, we hypothesize:

H3: Perceived reliability has a positive impact on attitudes towards Generative AI.

Perceived Creative Affordance and Attitude:

Perceived creative affordance refers to the users' recognition of Generative AI's ability to produce novel, innovative, and diverse content (Zhou and Fang, 2026). Prior research showed that technological creativity often inspires users by expanding the boundaries of what can be achieved, creating new opportunities for expression and problem-solving (Boateng, 2025). In the context of Generative AI, its capacity to generate original and personalized outputs enriches the user experience, providing both utilitarian and hedonic benefits (Gmiterek and Kotuła, 2025). Consequently, when users recognize the creative affordance of Generative AI, they are more inclined to develop a favorable attitude toward it. Hence, we hypothesize:

H4: Perceived creative affordance has a positive impact on attitude towards Generative AI.

Perceived Analysis Affordance and Attitudes:

Perceived analysis affordance refers to users' acknowledgment of Generative AI's ability to process information, identify needs, and provide accurate, actionable insights drawing upon accumulated knowledge and experience (Stahl and Eke, 2024). Previous research indicates that technologies with advanced analysis functions promote positive attitudes by improving efficiency, accuracy, and decision-making quality (Qiu *et al.,* 2026). Generative AI's ability to provide tailored recommendations or problem-solving pathways fosters a perception of competence and trustworthiness, which are essential for building favorable attitudes toward emerging technologies (Zhou *et al.,* 2025). Thus, we hypothesize:

H5: Perceived analysis affordance positively impacts attitude towards Generative AI.

Barriers:

Perceived Inertia and Attitude:

In the domain of online platforms, such as Generative AI, psychological barriers play a pivotal role in shaping users' acceptance and sustained use (Nel and Boshoff, 2020). Perceived inertia, characterized by a reluctance to deviate from established behaviors, may lead individuals to resist transitioning from traditional services to online-driven alternatives (Hsieh, 2015). People are often familiar with conventional methods and prefer known interaction patterns. Hence, we hypothesize:

H6: Perceived inertia negatively affects the users' attitudes toward Generative AI.

Perceived Threat and Attitude:

Similarly, perceived threat, encompassing concerns about privacy breaches, emotional inadequacy, and system reliability, may significantly hinder the adoption of Generative AI (Balakrishnan *et al.,* 2021). Users' apprehension about sharing sensitive personal and financial information, such as debit or credit card details, with systems, or doubts regarding the efficacy of non-human support mechanisms, can undermine trust and discourage engagement (Nel and Boshoff, 2020).

Therefore, we hypothesize:

H7: Perceived threat negatively affects users' attitude toward Generative AI.

Perceived Regret Avoidance and Attitude:

Additionally, perceived regret avoidance captures users' fear of making a poor decision that could lead to dissatisfaction or adverse outcomes (Samuelson and Zeckhauser, 1988). For Generative AI users, reliance on technology platforms may lead to inferior support compared to traditional services, fostering hesitation or avoidance (Nel and Boshoff, 2020).

Together, these barriers can negatively impact user evaluations of Generative AI, diminishing their persistent engagement. Addressing these concerns by reinforcing the platform's credibility, emotional safety, and data security promotes broader acceptance. Based on this rationale, we hypothesize:

H8: Perceived regret avoidance negatively affects users' attitude toward Generative AI.

Attitude and Continuance Intention:

Attitude is defined as learned, enduring, and evaluative predispositions that shape an individual's feelings, beliefs, and behavioral intentions toward a specific object, service, or technology (Davis, 1989). In Generative AI, attitude represents users' overall affective and cognitive evaluation of the platform and is crucial for determining subsequent behavioral outcomes. Positive attitude reflects favorable evaluations of the platform's value, usability, and relevance. It is a strong predictor of users' willingness to continue engaging with the service (Bhattacherjee, 2001).

Continuance intention refers to a user's deliberate intention to continue using a product or service after initial adoption. For Generative AI, users' continuance intention is critical because it ensures the successful survival of the business operation. Prior research has consistently shown that users with positive attitudes toward technology are more likely to develop strong continuance intentions, particularly for e-health, m-health, and digital therapy platforms (Bhattacherjee, 2001). Based on this rationale, we hypothesize:

H9: A positive user attitude toward Generative AI positively influences continuance intention to use the platform.

4. Research Methodology

4.1. Measurement of the Variables

To ensure content validity of the questionnaire, we adopted a multi-step validation procedure. All measurement items were adapted from well-established, widely cited scales in the prior literature. The core constructs used in the questionnaire are Perceived Interaction Quality (Pelau *et al.,* 2021), Perceived Personalization (Zhang *et al.,* 2014), Perceived Reliability (McKnight et al., 2002), Perceived Creativity Affordance (Dennis et al., 2012), Perceived Analysis Affordance (Sabherwal and Chan, 2001), Perceived Inertia (Hsieh and Lin, 2018), Perceived Threat (Balakrishnan *et al.*, 2021), Perceived Regret Avoidance (Tsiros and Mittal, 2000), Attitude (Schierz *et al,* 2010), and Repeated Use (Zanetta *et al.,* 2021). Each statement for each item was evaluated on a 7-point Likert scale. Respondents were instructed to indicate their degree of agreement with a series of statements.

Following Rahi's (2017) recommendations, the initial item pool was reviewed by three academic experts specializing in information systems and technology adoption. These experts evaluated the items for clarity, relevance, representativeness, and alignment with the underlying theoretical constructs.

We conducted a pilot test with 40 respondents who shared target group characteristics to further assess clarity and appropriateness. Feedback from the pilot test confirmed that items were clearly understood and adequately captured the intended constructs.

4.2. Sample Selection Process and Survey Technique

This research targeted Bangladeshis with experience using Generative AI. Because the data was anonymous, non-confidential, and did not involve any vulnerable participants, formal ethical approval was not required. A consent form was provided to each respondent before data collection for informed participation.

This study employed non-probability purposive sampling, a technique widely utilized in research examining technology use. This sampling method facilitates efficient data collection, enhances data quality, and provides greater control over sample selection (AbdulKareem and Oladimeji, 2024).

To identify potential participants, the researcher approached individuals in strategically chosen settings, including universities, corporations, and government institutions, where Generative AI applications were more likely in use. Participants were identified through direct contact, referrals, and professional networks.

The survey was disseminated exclusively through offline channels for greater control over sample quality and respondent authenticity. Paper-based questionnaires were distributed. The researcher personally introduced the study, explained its objectives, and provided participants with an informed consent form before their engagement.

Responses were obtained from 505 participants, a sample size that meets the recommended threshold (Deb and David, 2014). Data collection occurred from July to August 2025.

4.3. Data Analysis

The proposed conceptual model was examined using Partial Least Squares Structural Equation Modeling (PLS-SEM), a well-accepted method for analyzing a comprehensive research framework (Hair *et al.,* 2016). We performed the PLS-SEM analysis using Smart PLS version 4, a widely used tool for theory validation. PLS evaluates psychometric properties and provides strong evidence of the existence or nonexistence of associations (Fornell and Larcker, 1981). We followed the two-stage methodology presented by Anderson and Gerbing (1988). Initially, we conducted reliability and validity assessments utilizing a measurement model and evaluated the structural model to confirm the hypotheses.

4.4. Demographics

The demographics demonstrated comparatively balanced representation. Table 1 shows the demographic details.

Table 1: Summary of Demographics Data

		Frequency	***Percentage***
Gender	Female	209	41.4
	Male	296	58.6
Age	18 to 25 years	266	52.7
	26 to 35 years	164	32.5
	36 to 45 years	49	9.7
	46 to 55 years	21	4.2
	56 years or more	5	1.0
Living Area	Urban District	343	67.9
	Non-Urban District	162	32.1
Education Level	High School	26	5.1
	College	13	2.6
	Bachelor	262	51.9
	Masters	204	40.4
	PhD	0	0
	Others: Please Specify	0	0
Monthly Income	Less than BDT 50,000	158	31.3
	BDT 50,000-100,000	142	28.1
	BDT 100,000-200, 000	174	34.5
	BDT 200,000 and more	31	6.1
Generative AI Usage Experience	Less than 1 year	396	78.4
	1-3 years	109	21.6
	4-5 years	0	0
	5 years or more	0	0
Generative AI Using Frequency	Daily	109	21.6
	Weekly	78	15.4
	Monthly	205	40.6
	Yearly	113	22.4

5. Results

5.1. Common Method Bias

This study mitigated concerns regarding common method bias (CMB) (Podsakoff *et al.,* 2003). The respondents' personal data is maintained confidentially, and the sequence of items' generated questions is altered to prevent disclosing the conceptual framework. We conducted Harman's single-factor test to assess the probability of standard bias.

The results showed that a single factor accounted for 33.00% of the total variance, which is below the 50% threshold, confirming that CMB is unlikely to be a significant issue (Malhotra *et al.,* 2006). The variance inflation factor (VIF) values were examined to assess multicollinearity among indicators before the structural model analysis. As Hair *et al.* (2016) suggest, multicollinearity is problematic when VIF values exceed 3.3. According to Table 2, all indicator VIF values were below this threshold.

Table 2. The Measurement model: The Convergent validity of the constructs

Constructs	***Items***	***Outer loadings***	***VIF***	***Cronbach's Alpha***	***Composite Reliability, CR (rho_a)***	***Composite Reliability, CR (rho_c)***	***Average variance extracted (AVE)***
Attitude	ATT1	0.747	1.465	0.791	0.803	0.865	0.616
	ATT2	0.747	1.504				
	ATT3	0.873	2.061				
	ATT4	0.766	1.571				
Perceived Analysis Affordance	PAA1	0.780	1.362	0.707	0.716	0.836	0.630
	PAA2	0.839	1.466				
	PAA3	0.761	1.343				
Perceived Inertia	PI1	0.732	1.408	0.810	0.822	0.875	0.638
	PI2	0.846	1.798				
	PI3	0.763	1.821				
	PI4	0.848	2.278				
Perceived Interaction Quality	PIQ1	0.862	1.836	0.849	0.850	0.908	0.768
	PIQ2	0.877	2.227				
	PIQ3	0.889	2.277				
Perceived Personalization	PP1	0.769	1.423	0.776	0.792	0.855	0.596
	PP2	0.728	1.476				
	PP3	0.834	1.668				
	PP4	0.754	1.522				
Perceived Reliability	PR1	0.871	1.886	0.850	0.854	0.909	0.769
	PR2	0.879	2.273				
	PRI	0.880	2.161				
Perceived Regret Avoidance	PRA1	0.853	1.977	0.834	0.841	0.889	0.668
	PRA2	0.827	1.934				
	PRA3	0.764	1.585				
	PRA4	0.822	1.814				
	PCA1	0.880	2.239	0.880	0.882	0.926	0.806

Perceived Creativity Affordance	PCA2	0.910	2.612				
	PCA3	0.903	2.539				
Perceived Threat	PT1	0.853	1.906	0.850	0.877	0.897	0.686
	PT2	0.833	2.098				
	PT3	0.800	1.870				
	PT4	0.826	2.147				
Repeated Use	RU1	0.918	2.864	0.835	0.900	0.900	0.752
	RU2	0.937	3.052				
	RU3	0.732	1.491				

Note: Perceived Interactivity (PI), Perceived Personalization (PP), Perceived Credibility (PC), Perceived Creative Affordance (PCA), Perceived Analysis Affordance, (PAA), Attitude (ATT), Perceived Inertia (PIN), Perceived Threat (PT), Perceived Regret Avoidance (PRA), Repeated Use (RU)

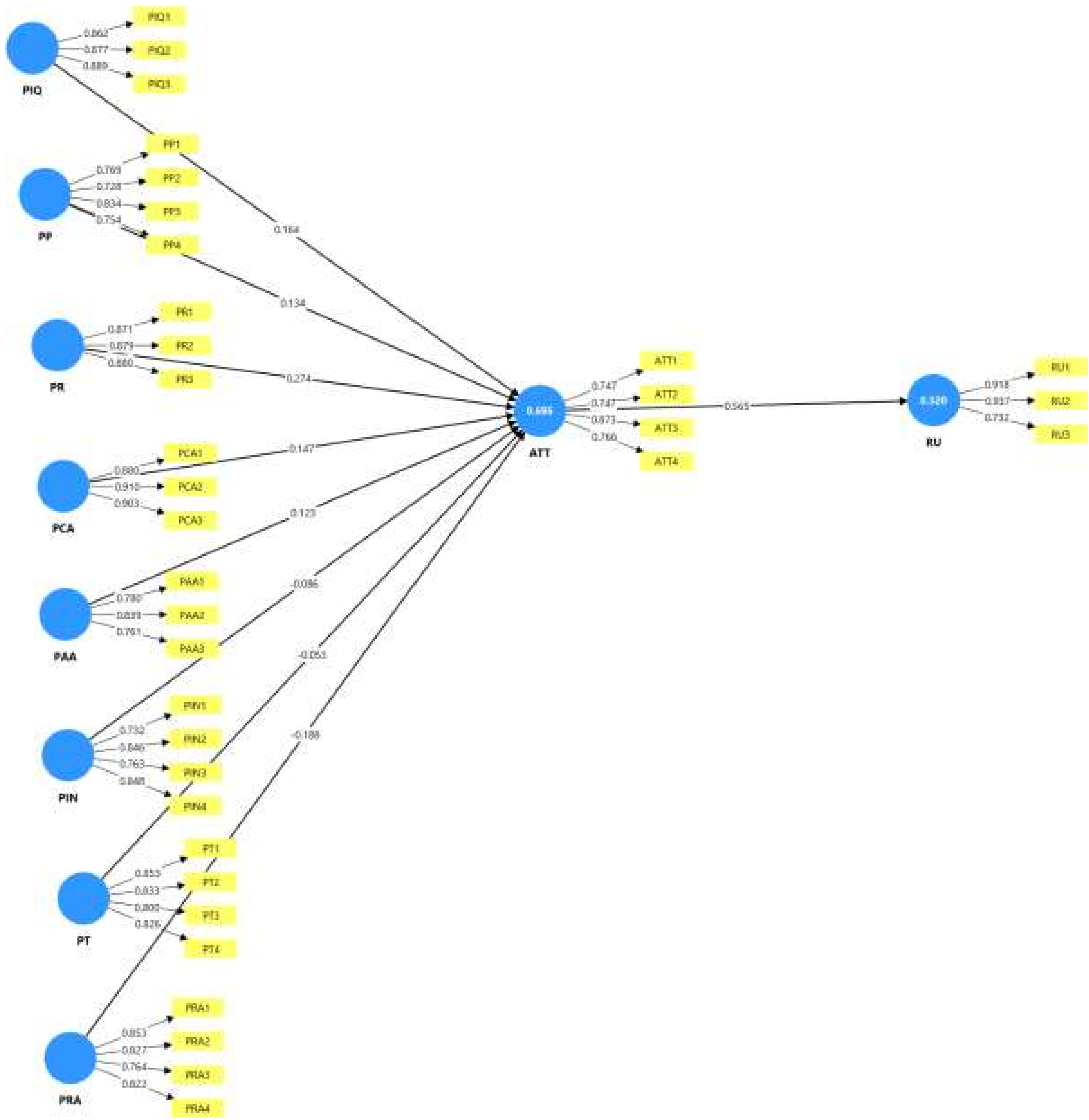

Figure 2: Graphical Output

5.2. Measurement Model Assessment

The indicator reliability, convergent validity, internal consistency, and discriminant validity of the measures were assessed. Table 2 illustrates the factor loadings, which denote the correlations between observed variables and their underlying latent constructs, ranging from 0.728 to 0.937. All values exceeded the recommended minimum of 0.70, demonstrating strong indicator reliability. Internal consistency was evaluated using Cronbach's alpha (α) and Composite Reliability (CR). The Cronbach's alpha values ranged between 0.707 and 0.880, while CR (rho_a) values fell between 0.716 and 0.900. CR (rho_c) values ranged from 0.836 to 0.926. All values surpassed the acceptable threshold of 0.70, confirming satisfactory reliability across the constructs. Additionally, the Average Variance Extracted (AVE) values ranged from 0.596 to 0.806, exceeding the 0.50 benchmark, affirming the convergent validity of the constructs (Hair *et al.,* 2016).

Table 3. Discriminant Validity - Fornell-Larcker Criteria

	ATT	*PAA*	*PI*	*PIQ*	*PP*	*PR*	*PRA*	*PCA*	*PT*	*RU*
ATT	0.785									
PAA	0.474	0.794								
PI	-0.238	-0.128	0.799							
PIQ	0.639	0.351	-0.083	0.876						
PP	0.585	0.290	-0.170	0.463	0.772					
PR	0.715	0.403	-0.170	0.537	0.500	0.877				
PRA	-0.686	-0.385	0.160	-0.663	-0.517	-0.604	0.817			
PCA	0.707	0.402	-0.139	0.588	0.612	0.720	-0.636	0.898		
PT	-0.078	-0.016	0.049	-0.062	0.010	-0.021	-0.005	-0.038	0.828	
RU	0.565	0.276	-0.201	0.486	0.389	0.503	-0.548	0.486	-0.051	0.867

Table 4. Discriminant Validity - Heterotrait-Monotrait ratio (HTMT).

	ATT	PAA	PI	PIQ	PP	PR	PRA	PCA	PT	RU
ATT										
PAA	0.630									
PI	0.296	0.167								
PIQ	0.776	0.453	0.101							
PP	0.736	0.383	0.203	0.552						
PR	0.860	0.519	0.197	0.623	0.607					
PRA	0.841	0.502	0.196	0.786	0.625	0.701				
PCA	0.839	0.510	0.162	0.674	0.729	0.833	0.735			
PT	0.092	0.066	0.065	0.075	0.035	0.036	0.034	0.043		
RU	0.668	0.356	0.229	0.552	0.453	0.580	0.627	0.548	0.063	

To confirm that the constructs are empirically distinct, discriminant validity was evaluated using two techniques. The Fornell-Larcker criterion (Fornell and Larcker, 1981) indicated that the square roots of the AVE values for each construct were greater than the correlations with other constructs (See Table 3). The Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015) was assessed, and all values were found to be below the 0.90 benchmark (See Table 4).

5.3. Structural Model Analysis

Hair *et al.* (2016) recommend conducting path analysis after the measurement model assessment. The hypothesized paths were tested using bootstrapping with 5,000 resamples, applying a 0.05 significance level. The model explained 69.5% of the variance in user attitudes and 32.0% of the variance in users' intentions to reuse Generative AI. The model's predictive capability was assessed through the Q^2 value (Stone, 1974), which should be greater than zero for each endogenous variable (Tenenhaus *et al.,* 2005). The Q^2 values obtained were 0.681 for attitudes and 0.338 for repeated use. All ten hypotheses were supported. (See Table 5.)

Table 5. Hypothesis test.

Hypothesis	*Path*	*Coefficient (B)*	*t-Statistics*	*P Values*	*Decision*	R^2	F^2	Q^2	*VIF*
H1	PIQ -> ATT	0.164	3.920	0.000	Supported	0.695	0.044	.681	2.003
H2	PP-> ATT	0.134	4.487	0.000	Supported		0.035		1.704
H3	PR -> ATT	0.274	7.013	0.000	Supported		0.107		2.317
H4	PCA -> ATT	0.147	3.303	0.001	Supported		0.025		2.826
H5	PAA -> ATT	0.123	3.700	0.000	Supported		0.039		1.268
H6	PI -> ATT	-0.086	2.883	0.004	Supported		0.023		1.054
H7	PT -> ATT	-0.053	2.036	0.042	Supported		0.009		1.013
H8	PRA -> ATT	-0.188	4.253	0.000	Supported		0.050		2.318
H9	ATT -> RU	0.565	18.742	0.000	Supported	0.320	0.470	.338	1.000

Note: Significant at $p < 0.05$

6. Discussion

This study examined how both facilitators and barriers influence users' attitudes and intentions to continue using Generative AI. While prior research has tended to emphasize enablers, our findings show that inhibitors are also decisive in post-adoption behaviors.

The results confirm that (H1) perceived interaction quality significantly enhances users' attitude toward Generative AI platforms. This finding suggests that when users perceive the system as responsive, intuitive, and engaging, they are more likely to form favorable evaluations. This result is consistent with prior post-adoption studies (Zhou and Ma, 2025). For platform designers, this result underscores the importance of investing in seamless interaction flows and reduced cognitive effort.

(H2) Perceived personalization also demonstrated a significant positive impact on user attitude. This result highlights that users value Generative AI's ability to adapt responses and recommendations to individual needs, preferences, and contexts. These findings align with prior work on personalization in digital platforms, where tailored outputs were shown to enhance trust, enjoyment, and long-term commitment (Zhou and Ma, 2025). Theoretically, personalization functions as a utilitarian mechanism and an affective catalyst, simultaneously enhancing trust and fostering user satisfaction. Practically, personalization offers a pathway for service providers to differentiate their platforms in increasingly competitive markets.

(H3) Perceived reliability emerged as another critical enabler of positive attitudes. Users who perceive Generative AI as accurate, consistent, and trustworthy in its outputs are more likely to view the technology favorably. This result resonates with information science and systems research, which emphasizes that reliability mitigates uncertainty and risk perceptions, encouraging sustained use (Zhou and Ma, 2025). This finding also strengthens arguments that trust-building mechanisms must be central to AI adoption models. Practically, developers and policymakers should focus on transparency, data protection standards, and reliability to foster user confidence.

The significant effect of (H4) perceived creative affordance illustrates that users appreciate the technology's potential to support creativity, problem-solving, and self-expression. Generative AI is perceived as more than a transactional tool. It enables users to experiment with new ideas and novel content and extend their creative capacities. This finding resonates with studies highlighting how innovation compatibility drives engagement (Zhou *et al.*, 2025). In practice, this point suggests that platforms should position themselves as creativity enablers useful in education, the arts, and content creation.

(H5) Perceived analysis affordance significantly shaped positive user attitude. Users value AI's capacity to process complex information, detect patterns, and provide actionable insights, which enhances decision-making and problem-solving. This confirms prior findings that analytical competence is a core attribute of AI systems, user trust, and engagement (Zhou *et al.,* 2025). In education, business, and healthcare, the analytical affordance of Generative AI is particularly relevant. This point strengthens the argument that affordance perspectives must consider both the technology's creative and analytical roles. In practice, it suggests that Generative AI platforms should emphasize their analytical capabilities, where evidence-based solutions are critical.

On the other hand, this study also highlights the critical role of psychological barriers.

Perceived inertia (H6) emerged as a significant negative influence on user attitudes towards Generative AI. This result is consistent with previous research, which has shown that individuals tend to resist changing familiar behaviors even when new technologies offer convenience and additional benefits (Chakraborty *et al.,* 2024).

Perceived threat (H7) also negatively impacts users' attitudes. This outcome is consistent with prior research, which found that on online platforms, where sensitive personal and financial information is routinely shared, users may fear potential breaches (Chakraborty *et al.,* 2024). Theoretically, this finding highlights the dual nature of technological affordances, which simultaneously enable user empowerment while eliciting anxiety. In practice, it requires establishing robust governance mechanisms, transparent articulation of safety protocols, and demonstrable security measures to mitigate perceived risks.

Perceived regret avoidance (H8) was identified as a deterrent to favorable attitude. This result is consistent with other studies demonstrating that users may hesitate to adopt or continue using Generative AI due to fear that their choice might lead to poorer outcomes than traditional retail services (Chakraborty *et al.,* 2024). This finding extends continuance models by integrating regret-related barriers. Practically, it suggests that service providers should offer reassurance through trial opportunities, error-correction features, and transparent performance comparisons to reduce regret-related concerns.

This study underscores the strong positive impact of (H9) attitude on the continuance intention to use Generative AI. This finding is consistent with prior research, which highlighted the central role of user attitudes, perceived value, and emotional experiences that drive long-term user loyalty and advocacy (Mason *et al.,* 2023). This finding reinforces the post-adoption explanatory power of the ELM and SQB, indicating that beyond improving technical features, sustained use is primarily driven by trust, personalization, and creative engagement that foster positive user attitude.

7. Implications

7.1. Theoretical Implications

This study added several significant values to the information science literature by applying a dual-factor approach through the ELM and SQB Theories.

First, this research demonstrated how facilitator-barrier factors concurrently shape user attitudes toward the continued use of Generative AI. While, previous researches presented a segmented view of either facilitators or barriers, this study embraces an integrated perspective and provides a more comprehensive insights of technology post adoption in Generative AI domain.

Second, this research applied ELM as enablers and SQB as inhibitors to ensure deeper theoretical underpinnings of facilitator-barrier approach and thereby, addressed a notable gap in the existing literature. Moreover, this dual-process perspective captures the complexity of real-world decision-making more accurately than models focused solely on enablers.

Third, this study demonstrated how enabler perceptions, such as, perceived interaction quality, perceived personalization, perceived reliability, perceived creativity affordance, perceived analysis affordance, and inhibitor perceptions, for instance, perceived inertia, perceived threat, perceived regret avoidance, shape user attitudes toward Generative AI. By applying these facilitators, this research highlights how technology-based perceptions vary across users, particularly in Generative AI products where individual needs and priorities are highly differentiated. On the other hand, by examining the barriers, this research offers insights form psychological and cognitive biases that deter the adoption of Generative AI technologies.

Fourth, another novel contribution of this study is the emphasis on continuance intention as a key "Response" variable within the proposed framework. While previous research predominantly focused on initial adoption or usage intention, this study highlights continuance intention as a critical factor for the long-term diffusion and success of Generative AI.

Fifth, although the ELM and SQB have been applied in various research domains, their applications to the context of Generative AI adoption remain limited. By adopting this approach, the research provides a more dynamic and comprehensive understanding of the emotional and cognitive processes underlying users' continued engagement with Generative AI.

7.2. Managerial Implications

The results of this study offer several important implications for developers, platform owners, and policymakers seeking to strengthen user engagement and sustained adoption of Generative AI platforms.

First, the positive influence of perceived interaction quality underscores the need for Generative AI providers to design highly responsive, intuitive, and seamless interaction environments. Improving the speed, clarity, and relevance of system responses can significantly enhance user satisfaction and promote favorable attitudes. Investing in natural language processing, error-free responses, and adaptive interaction flows will ensure that users feel understood and supported throughout their usage experience.

Second, the significant effect of perceived personalization indicates that tailoring content, recommendations, and outputs to individual needs can enhance users' evaluations of the platform. Managers should adopt advanced personalization algorithms, allow customizable preferences, and enable context-sensitive suggestions to strengthen perceived relevance. Transparent personalization features can help users feel that the AI system is specifically designed to support their unique tasks and goals.

Third, the positive relationship between perceived reliability and user attitude reveals that accuracy, consistency, and trustworthiness are central to users' acceptance of Generative AI. Platform developers should ensure high-quality training data, rigorous testing, and continuous performance monitoring to minimize errors and inconsistencies. Clear communication about reliability measures, system accuracy, and limitations can also reinforce user confidence and reduce uncertainty.

Fourth, the finding on perceived creative affordance suggests that users appreciate AI systems that stimulate creativity and enable novel idea generation. To leverage this, managers should integrate features that support brainstorming, creative writing, visual content generation, and problem-solving tasks. Allowing experimentation, offering creative templates, and showcasing inspiring use cases can further amplify users' perception of the platform as a tool for innovation.

Fifth, the impact of perceived analysis affordance shows that users value Generative AI for its analytical capabilities, such as summarization, reasoning, forecasting, and data interpretation. Strengthening these features through advanced model fine-tuning, domain-specific knowledge modules, and improved factual reasoning can enhance perceived utility. Providing explainable AI outputs may also increase analytical trust and encourage greater reliance on the platform for complex decision-making tasks.

On the other hand, the negative role of perceived inertia highlights that habitual resistance or comfort with traditional tools may prevent users from developing positive attitudes toward Generative AI. Managers should incorporate onboarding support, guided tutorials, and gradual learning curves to ease transitions from existing technologies.

Similarly, the negative influence of perceived threat indicates that fears related to job displacement, loss of control, privacy concerns, or ethical implications may undermine user attitudes. Managers and policymakers must communicate transparently about data usage, privacy safeguards, and responsible AI practices.

Additionally, perceived regret avoidance negatively affects user attitudes, suggesting that users hesitate when they fear making the wrong decision with AI-generated outputs. To address this, platforms should highlight verification features, provide alternative suggestions, and offer confidence scores or justification mechanisms. Educating users about how AI recommendations are generated can reduce decision-related anxiety and increase comfort with using the system.

Moreover, the strong positive relationship between attitude and continuance intention reinforces the importance of cultivating favorable user perceptions to ensure long-term engagement. Managers must continuously monitor user satisfaction, enhance value-added features, and maintain transparent communication to build positive evaluations of Generative AI. Effective marketing, user success stories, and social proof can amplify positive attitudes and encourage repeated use.

8. Limitations and Future Research

This study has several shortcomings that must be acknowledged. The findings may have limited generalizability, as data collection was confined to a specific community. In the future, scholars should aim to validate and extend these results by examining more diverse populations across different cultural and geographical contexts. Second, the use of self-administered questionnaires raises the risk of social desirability bias, which can affect response accuracy. future studies could utilize more objective data sources, to complement or validate self-reported measures. This study did not incorporate several potentially influential factors that could shape users' attitudes toward their intention to continue using Generative AI. Future research should investigate the role of sociocultural variables, digital confidence, and concerns around data privacy. Finally, scholars might investigate the influence of policy interventions aimed at understanding usage inhibitors on users' attitudes toward their intention to continue using Generative AI.

9. Conclusion

This research aimed to examine the key motivators and impediments that persuade users to continue using Generative AI. The outcomes suggested that perceived interaction quality, perceived personalization, perceived reliability, perceived creative affordance, and perceived analysis affordance are critical drivers that positively shape user attitudes toward continued engagement. Conversely, traditional resistance factors, including perceived inertia, perceived threat, and regret avoidance, were identified as significant barriers impeding post-adoption. The study also confirmed that users' attitudes significantly influence their intentions to persist in use, highlighting the importance of fostering positive perceptions to encourage sustained use. These insights carry important implications for platform developers, enterprise owners, and policymakers aiming to promote Generative AI solutions. By strategically enhancing the enabling factors and addressing the psychological and technological barriers, stakeholders can improve user acceptance and long-term engagement with these platforms.

Future researchers should further explore these dynamics across different populations and settings, incorporating additional variables such as digital confidence, trust, and cultural differences, to provide more inclusive insights into the factors driving the adoption and continuance of Generative AI.

References

AbdulKareem, A. K. and Oladimeji, K. A. (2024), "Cultivating the digital citizen: trust, digital literacy and e-government adoption", *Transforming Government People Process and Policy*, Vol. 18 No. 2, pp. 270-286, doi:10.1108/tg-11-2023-0196.

Anderson, J. C. and Gerbing, D. W. (1988), "Structural equation modeling in practice: A review and recommended two-step approach", *Psychological Bulletin,* Vol.103 No.3, pp. 411–423, doi:10.1037/0033-2909.103.3.411.

Baig, M. I. and Yadegaridehkordi, E. (2025), "Factors influencing academic staff satisfaction and continuous usage of generative artificial intelligence (GenAI) in higher education", *International Journal of Educational Technology in Higher Education*, Vol. 22 No. 1, pp. 310-329, doi:10.1186/s41239-025-00506-4.

Balakrishnan, J., Dwivedi, Y. K., Hughes, L., and Boy, F. (2021), "Enablers and inhibitors of AI- powered voice assistants: A dual-factor approach by integrating the status quo bias and technology acceptance model", *Information Systems Frontiers*, Vol 21 No. 4, pp. 1–22, doi: 10.1007/s10796-021-10203-y.

Bhattacherjee, A. (2001), "Understanding Information Systems Continuance: An Expectation-Confirmation Model", *MIS Quarterly*, Vol. 25 No. 3, pp. 351, doi:10.2307/3250921.

Boateng, F. (2025), "The transformative potential of Generative AI in academic library access services: Opportunities and challenges", *Information Services & Use*, Vol. 45. No. 02, pp. 140–147, doi:10.1177/18758789251332800.

Chakraborty, D., Kar, A. K., Patre, S. and Gupta, S. (2024), "Enhancing trust in online grocery shopping through generative AI chatbots", *Journal of Business Research*, Vol. 180 No. 11, pp. 114-137, doi:10.1016/j.jbusres.2024.114737.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol.13 No. 3, pp. 319-340, doi: 10.2307/249008.

Deb, M. and Lomo-David, E. (2014), “An empirical examination of customers’ adoption of m-banking in India”, *Marketing Intelligence and Planning*, Vol. 32 No. 4, pp. 475–494, doi:10.1108/mip-07-2013-0119.

Dennis, A. R., Minas, R. K. and Bhagwatwar, A. (2012), “Sparking creativity: Improving electronic brainstorming with individual cognitive priming”, *2012 45th Hawaii International Conference on System Sciences*, pp. 139-148, doi:10.1109/hicss.2012.541.

Fornell, C. and Larcker, D.F. (1981), “Evaluating Structural Equation Models with Unobservable Variables and Measurement Error”, *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39–50, doi:10.2307/3151312.

Gmiterek, G. and Kotuła, S.D. (2025), “Generative artificial intelligence in the activities of academic libraries of public universities in Poland”, *The Journal of Academic Librarianship*, Vol. 51 No. 3, pp.103-143. doi:10.1016/j.acalib.2025.103043.

Hair, J. F., Hult, G. T. M., Ringle, C. M. and Sarstedt, M. (2016), “A primer on partial least squares structural equation modeling (PLS-SEM)”, *SAGE Publications Ltd*. Available at: https://uk.sagepub.com/en-gb/eur/a-primer-on-partial-least-squares-structural-equation-modeling-pls-sem/book270548.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), “A new criterion for assessing discriminant validity in variance-based structural equation modeling”, *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp.115–135, doi:10.1007/s11747-014-0403-8.

Hsieh, P. J. (2015), “Healthcare professionals’ use of health clouds: Integrating technology acceptance and status quo bias perspectives”, *International journal of medical informatics*, Vol. 84 No. 7, pp. 512–523, doi:10.1016/j. ijmedinf.2015.03.004.

Hsieh, P. J. and Lin, W. S. (2018), “Explaining resistance to system usage in the Pharma Cloud: A view of the dual-factor model”, *Information and Management*, Vol. 55 No. 1, pp. 51–63, doi:10.1016/j.im.2017.03.008.

Khan, A. R. and Furuoka, F. (2025), “Gen Z consumers' continuance intention to use online second-hand luxury (OSHL) platforms: A conceptual framework”, *International Journal of Business Information Systems*, Vol. 51 No. 1, doi:10.1504/IJBIS.2025.10070009.

Khan, A. R., Furuoka, F. and Rasiah R. (2025), “Understanding Gen Z Consumers’ Continuance Intention to Use ChatGPT: A Conceptual Framework”, *International Journal of Business Information Systems*, Vol. 51 No. 2, doi: 10.1504/IJBIS.2025.10073992.

Khan, A. R., Furuoka, F., Rasiah R. and Hossain, S. (2025), “Investigating User Continuance in Second-Hand Trading Platforms: An Integrated Multidimensional Study”, *International Journal of Electronic Business,* Vol. 51 No. 2, doi: 10.1504/IJEB.2026.10076724.

Kim, D., Kim, S., Kim, S. and Lee, B. H. (2024), “Generative AI characteristics, user motivations, and usage intention”, *Journal of Computer Information Systems*, Vol. 21 No. 3, pp. 1–16, doi:10.1080/08874417.2024.2442438.

Malhotra, N.K., Kim, S.S. and Patil, A. (2006), “Common Method Variance in IS Research: A Comparison of Alternative Approaches and a Reanalysis of Past Research”, *Management Science*, 52(12), pp.1865–1883, doi:10.1287/mnsc.1060.0597.

Mason, M.C., Oduro, S., Umar, R.M. and Zamparo, G. (2023), “Effect of consumption values on consumer behavior: a Meta-analysis”, *Marketing Intelligence & Planning*, Vol. 41 No. 7, pp. 923-944, doi:10.1108/MIP-03-2023-0100.

Harrison McKnight, D., Choudhury, V. and Kacmar, C. (2002), “The impact of initial consumer trust on intentions to transact with a web site: a trust building model”, *The Journal of Strategic Information Systems*, Vol. 11 No. 3, pp. 297–323, doi:10.1016/s0963-8687(02)00020-3.

Nel, J., and Boshoff, C. (2020), “Status quo bias and shoppers’ mobile website purchasing resistance”, *European Journal of Marketing*, Vol. 54 No. 6, pp. 1433–1466, doi: 10.1108/EJM-02-2018-0144.

Pelau, C., Dabija, D.-C. and Ene, I. (2021), “What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry”, *Computers in Human Behavior*, Vol. 122 No. 10, pp.106-155, doi:10.1016/j.chb.2021.106855.

Petty, R. E. and Cacioppo, J. T. (1981), “Issue involvement as a moderator of the effects on attitude of advertising content and context”, *Advances in Consumer Research,* Vol. 8, pp. 20–24.

Podsakoff PM, MacKenzie SB, Lee J-Y. and Podsakoff NP. (2003), “Common method biases in behavioral research: A critical review of the literature and recommended remedies”, *Journal of applied psychology*, Vol. 88 No. 5, pp.879, doi:10.1037/0021-9010.88.5.879 PMID: 14516251.

Qiu, J., Zhang, T., Xu, Z., Fu, Y., Mi, Q. and Li, S. (2026), "Understanding users’ online health information seeking switching intention: from traditional health information platforms to GAI". *Online Information Review*, Vol. 50 No. 1 pp. 18–36, doi: 10.1108/OIR-11-2024-0706.

Rahi, S. (2017), “Research Design and Methods: a Systematic Review of Research Paradigms, Sampling Issues and Instruments Development”, *International Journal of Economics and Management Sciences*, Vol. 06 No. 02, pp. 1–5, doi:10.4172/2162-6359.1000403.

Sabherwal, R. and Chan, Y. E. (2001), “Alignment between business and IS strategies: A study of prospectors, analyzers, and defenders”, *Information Systems Research*, Vol. 12 No. 1, pp. 11-33, doi:10.1287/isre.12.1.11.9714.

Samuelson, W., and Zeckhauser, R. (1988), “Status quo bias in decision making”, *Journal of risk and uncertainty*, Vol.1 No.1, pp. 7–59, doi:10.1007/BF00055564.

Schierz, P.G., Schilke, O. and Wirtz, B.W. (2010), “Understanding consumer acceptance of mobile payment services: an empirical analysis”, *Electronic Commerce Research and Applications*, Vol. 9 No. 3, pp. 209-216, doi: 10.1016/j.elerap.2009.07.005.

Shahzad, K., Khan, A. N., Ahmad, B., Hayat, K. and Chang, S. (2025), “Balancing trust and distrust in generative AI chatbot adoption: a case study from China”, *Service Industries Journal*, Vol. 21 No. 3, pp. 1–24, doi:10.1080/02642069.2025.2487819.

Stahl, B. C. and Eke, D. (2024), “The ethics of ChatGPT – Exploring the ethical issues of an emerging technology”, *International Journal of Information Management*, Vol. 74 No. 4, pp. 102700, doi:10.1016/j.ijinfomgt.2023.102700.

Sun, Y., Fan, Z., Sheng, D., Zhang, X. and Xu, F. (2026), "Interactive perceptions and persuasion: how AI-generated content influences users", *The Electronic Library*, Vol. 44 No. 1 pp. 109–135, doi: 10.1108/EL-05-2025-0172.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y., and Lauro, C. (2004), “PLS path modeling”, *Computational Statistics and Data Analysis*, Vol. 48 No. 1, pp. 159–205. Doi:10.1016/j.csda.2004.03.005.

Tsiros, M. and Mittal, V. (2000), “Regret: A model of its antecedents and consequences in consumer decision making”, *Journal of Consumer Research*, Vol. 26 No. 4, pp. 401–417, doi.org/10.1086/209571.

Wang, D., Guo, J., Zheng, K. and Deng, X. (2026), "AI or human? A study of university students’ awareness of library reference service agents", *The Electronic Library*, Vol. 44 No. 1 pp. 136–154, doi: 10.1108/EL-06-2025-0230.

Zanetta, L.D., Hakim, M.P., Gastaldi, G.B., Seabra, L.M.J., Rolim, P.M., Nascimento, L.G.P., Medeiros, C.O. and da Cunha, D.T. (2021), “The use of food delivery apps during the COVID-19 pandemic in Brazil: the role of solidarity, perceived risk, and regional aspects”, *Food Research International*, Vol. 149 No. 2, pp. 110671, doi: 10.1016/j.foodres.2021.110671.

Zhang, H., Lu, Y., Gupta, S. and Zhao, L. (2014), “What motivates customers to participate in social commerce? The impact of technological environments and virtual customer experiences”, *Information and Management*, Vol. 51 No. 8, pp. 1017-1030, doi: 10.1016/j.im.2014.07.005.

Zhang, Y., Liu, Y., Li, W., Peng, L. and Yuan, C. (2020), "A study of the influencing factors of mobile social media fatigue behavior based on the grounded theory", *Information Discovery and Delivery*, Vol. 48 No. 2 pp. 91–102, doi10.1108/IDD-11-2019-0084.

Zhou, T. and Fang, X. (2026), "Understanding user trust in AI-generated content: an elaboration likelihood model perspective", *Online Information Review*, Vol. 50 No. 1 pp. 171–188, doi: 10.1108/OIR-01-2025-0041.

Zhou, J., Lu, Y. and Chen, Q. (2024), “GAI Identity Threat: When and Why Do Individuals Feel Threatened?”, *Information & Management*, Vol. 82 No. 2, pp.104093–104093, doi: 10.1016/j.im.2024.104093.

Zhou, T. and Ma, X. (2025), “Examining generative AI user continuance intention based on the SOR model”, *Aslib Journal of Information Management*, Vol. 43. No. 4, pp. 120–154, Doi:10.1108/AJIM-08-2024-0620.