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A Study on Factors Influencing Continuous Usage Intention of Chatbot Services in South Korean Financial Institutions

Yeun-su Choi ¹, Seung-zoon Lee ² and Jeongil Choi ^{3,*} 

¹ Department of IT Policy and Management, Graduate School of Soongsil University, 369 Sangdo-ro, Dongjak-gu, Seoul 06978, Republic of Korea; yeunsu0918@soongsil.ac.kr

² Department of Business Administration, Graduate School of Soongsil University, 369 Sangdo-ro, Dongjak-gu, Seoul 06978, Republic of Korea; zoon@soongsil.ac.kr

³ School of Business Administration, Soongsil University, 369 Sangdo-ro, Dongjak-gu, Seoul 06978, Republic of Korea

* Correspondence: jichoi@ssu.ac.kr; Tel.: +82-2-820-0561

Abstract: The South Korean AI market has grown significantly, yet while chatbot adoption is well-studied, sustained use remains underexplored. This study surveyed 250 financial institution chatbot users in South Korea in February 2024, using SPSS and R to investigate quality effects on intention of continuous usage. Results showed that social presence, response accuracy, assurance, and interactivity positively influenced expectation confirmation. In contrast, responsiveness, reliability, and usability had no significant effect, while security negatively impacted frequent users, reflecting trust concerns. These findings guide financial institutions in enhancing chatbot retention through interactivity and trust. Conducted in a pre-generative AI context, this study suggests future longitudinal research to address evolving AI technologies and user behaviors.

Keywords: financial institutions; information system success model; continuous usage intention; post-acceptance model; service quality



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1. Introduction

The rapid growth of artificial intelligence (AI) technologies is driving innovation across the financial sector. In South Korea, the domestic AI market grew from KRW 1.5 trillion (approximately USD 1.03 billion) in 2019 to KRW 3.2 trillion (approximately USD 2.2 billion) in 2021. The financial AI market alone doubled from KRW 300 billion (approximately USD 207 million) to KRW 600 billion (approximately USD 414 million) during the same period (Hong, 2022). This rapid growth highlights AI's transformative role in enhancing customer experiences and institutional competitiveness.

A notable example is KB Kookmin Bank's AI chatbot "Bibi", which has improved service quality and market competitiveness through personalized consultations. Such advancements demonstrate that chatbots are becoming indispensable for meeting customer needs and accelerating digital transformation in financial services.

As face-to-face interactions give way to non-face-to-face channels, the importance of AI-driven chatbot systems is increasingly clear (Expert Market Research, 2024). However, while studies on chatbot adoption and acceptance are abundant, research on factors sustaining their continuous usage remains limited. Without addressing this gap, financial institutions may fail to maximize the long-term benefits of chatbot services.

This study examines how financial chatbot characteristics shape users' intentions to continue using them in South Korea, a market distinct from Europe's regulation-centric

approach. Unlike previous studies that focus on initial adoption, this research delves into sustained engagement, providing strategic insights for enhancing chatbot services. We propose that service characteristics (e.g., social presence) and system quality (e.g., interactivity) drive continuous usage through mechanisms like expectation confirmation, perceived usefulness, and satisfaction. These findings shed light on digital transformation in the financial sector and offer practical recommendations for improving service quality, customer satisfaction, and market competitiveness.

2. Theoretical Background

This study integrates multiple theoretical frameworks to examine the continuous usage intention of financial chatbot services in South Korea, contrasting with Europe's regulatory focus. The Post-Acceptance Model (PAM) explains sustained usage through expectation confirmation, perceived usefulness, and satisfaction (Bhattacharjee, 2001), while the SERVQUAL model evaluates service quality via dimensions like assurance and responsiveness (DeLone & McLean, 2003). The Information System Success Model (IS-Success) further assesses system quality, including security and interactivity (DeLone & McLean, 1992). These models collectively address the gap in prior research, which predominantly focuses on initial adoption (S. H. Park, 2023), by emphasizing sustained engagement critical to South Korea's branch reduction context. Unlike Europe, where GDPR compliance shapes chatbot deployment, South Korea prioritizes operational efficiency and user retention, necessitating a tailored theoretical lens.

2.1. Chatbot Services: Concept and Necessity in Financial Institutions

A chatbot, a combination of "chatting" and "robot", is an interactive system designed to answer user inquiries through dialogue (Jung, 2019). Chang (2016) defines chatbots as AI-based software that provides information through text-based conversations. Initially limited to text, chatbots have now evolved to incorporate voice support, expanding their scope (J. H. Park et al., 2019).

Chatbots primarily automate consumer consultations. Unlike traditional phone or email support, they provide instant assistance through online chats on mobile devices or PCs, enhancing service efficiency (Seo, 2018; Hill et al., 2015). Modern chatbots can understand user queries and offer optimal answers, engaging in two-way communication to deliver tailored solutions (Ashfaq et al., 2020). Such interactions build "social presence", where users view chatbots as partners, leading to higher satisfaction and usage intention (Ashfaq et al., 2020). For instance, Ashfaq et al. (2020) found users interacting with high-presence chatbots reported a 25% increase in satisfaction.

The financial industry has expanded chatbot use significantly amid digital transformation. The COVID-19 pandemic accelerated demand for non-face-to-face services, shifting the focus to digital channels. Between 2019 and 2023, South Korean banks closed 965 branches and cut 5635 jobs, signaling a transition to digital services as shown in Figure 1 (Expert Market Research, 2024). For example, KB Kookmin Bank's chatbot improved efficiency and customer satisfaction.

Chatbots are emerging as "online tellers" capable of handling tasks like authentication, transaction verification, and document preparation. S. E. Lee (2022) shows that chatbots reduce operational costs by 30% and provide 24/7 support, enhancing customer engagement and solidifying their role in the financial sector's digital transformation.

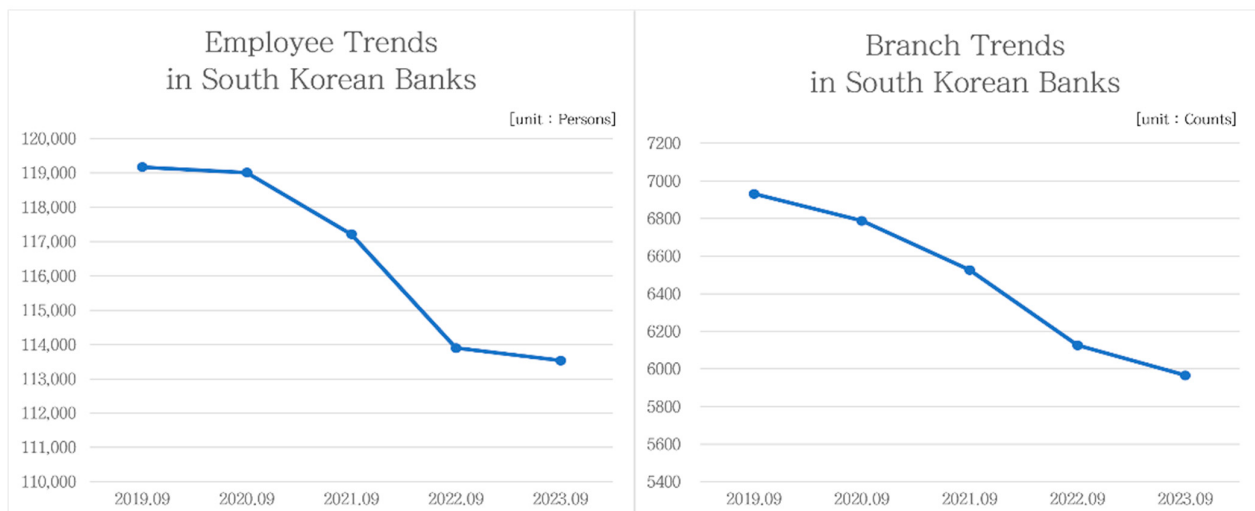


Figure 1. Employee and branch trends in South Korean banks (2019–2023).

2.2. Literature Review

2.2.1. Chatbot Services in Financial Institutions

The domestic financial industry has rapidly adopted chatbot services in response to the rising demand for non-face-to-face services (S. E. Lee, 2022). This trend has extended from first-tier institutions to second-tier institutions. Chatbots are employed by financial institutions to enhance customer experience and service quality (Bhattacharjee, 2001). The COVID-19 pandemic has accelerated preference for non-face-to-face channels, resulting in increased bank branch closures (H. Y. Lee, 2023). Consequently, chatbots have become crucial “online tellers”, managing tasks such as authentication, transaction verification, and document processing (Garrison et al., 2000; S. E. Lee, 2022). Chatbots enhance operational efficiency by providing 24/7 customer support, reducing labor costs, and improving the speed of problem resolution (S. E. Lee, 2022). Previous studies, as summarized in Figure 2, highlighted social presence and response accuracy as key characteristics of financial chatbots. For instance, Konya-Baumbach et al. (2023) emphasized that social presence and chatbot identity enhance user engagement, though their study lacks empirical validation in financial contexts. Similarly, T. H. Kim et al. (2020) identified response accuracy and social presence as critical for user satisfaction and data protection, but overlooked generative AI advancements. These findings align with social presence theory (Oghuma et al., 2016), which emphasizes the role of social presence in fostering user engagement, and information processing theory (Miller, 1956; Lin et al., 2005), which underscores the importance of response accuracy for effective information processing. These studies underscore the need for context-specific research that examines long-term user retention, which this study addresses by focusing on the sustained usage of financial chatbot services.

2.2.2. Service Quality Measurement Model (SERVQUAL Model)

While the SERVQUAL model was originally developed by Parasuraman et al. (1988), recent studies have extended it to the context of financial chatbots. It builds on the expectation disconfirmation theory (Oliver, 1980) and research by Grönroos (Byun & Cho, 2020). Previous studies, as summarized in Figure 3, highlighted assurance and responsiveness as key service characteristics across various contexts. For instance, Nguyen et al. (2021) and J. T. Kim and Choi (2022) used reliability, assurance, responsiveness, empathy, and tangibility as independent variables in bank and airline chatbots, respectively, demonstrating their positive impact on trust, satisfaction, perceived usefulness, ease of use, and usage intention. Meanwhile, studies in other industries, such as Huang (2022) on sports centers and B. Han

[et al. \(2016\)](#) on IT management services, also emphasize assurance and responsiveness as core dimensions of service quality, suggesting their applicability to chatbot services. Additionally, [J. T. Kim and Choi \(2022\)](#) analyzed the impact of chatbot service quality on continuous usage intention, highlighting the moderating role of social presence, which amplifies the positive effect of quality when perceived social presence is high. In contrast, [Jeong et al. \(2023\)](#) emphasized that both service quality and service value significantly influence continuous usage intention, with service value acting as a key mediator between quality and intention. These studies collectively underscore the role of quality in chatbot retention but highlight different mechanisms—social presence as a moderator and service value as a mediator—in explaining sustained usage in financial contexts. These findings align with service quality theory ([DeLone & McLean, 2003](#)), which posits that dimensions like assurance and responsiveness are critical for fostering user satisfaction and trust in service interactions. In contrast, this study leverages these variables to represent chatbot service quality in financial institutions, addressing the gap in longitudinal research.

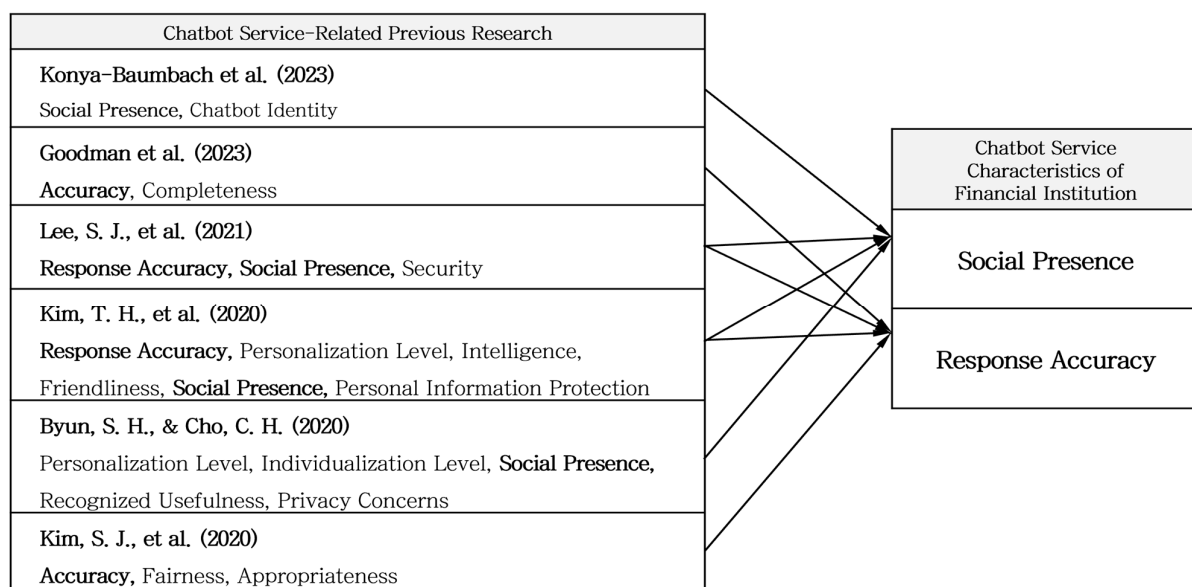


Figure 2. Key variables identified from chatbot service research. Based on [Konya-Baumbach et al. \(2023\)](#), [Goodman et al. \(2023\)](#), [S. J. Lee et al. \(2021\)](#), [T. H. Kim et al. \(2020\)](#), [Byun and Cho \(2020\)](#), [S. J. Kim et al. \(2020\)](#).

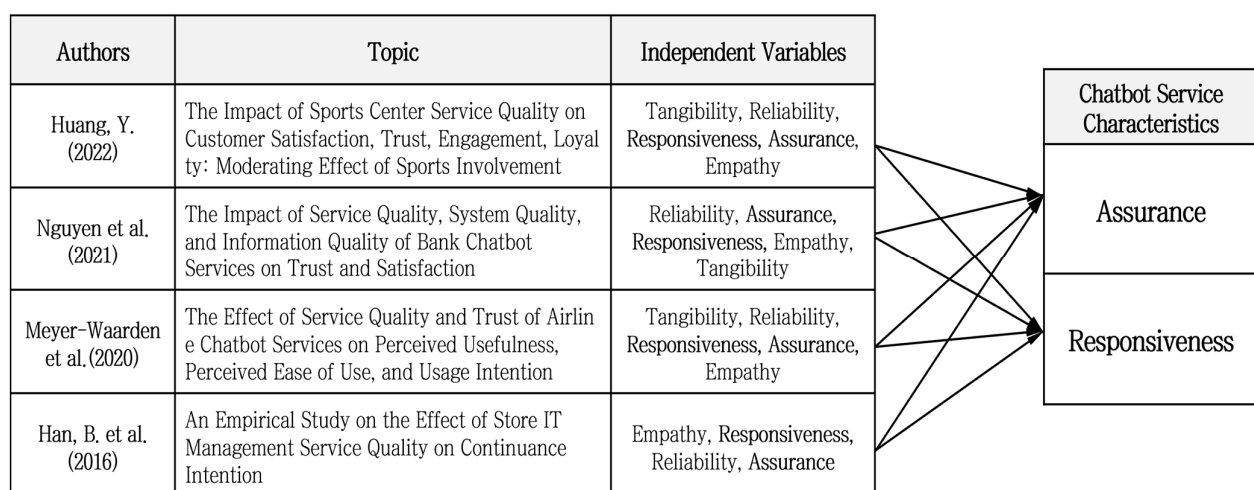


Figure 3. Key Variables Identified from the SERVQUAL Model. Based on [Huang \(2022\)](#), [Nguyen et al. \(2021\)](#), [Meyer-Waarden et al. \(2020\)](#), [B. Han et al. \(2016\)](#).

2.2.3. Information System Success Model (IS-SUCCESS Model)

The Information Systems Success Model is used to comprehensively evaluate system quality, information quality, and service quality (DeLone & McLean, 1992). This model was expanded by (Grönroos, 1984) and (Nguyen et al., 2021), and the revised model by DeLone and McLean (1992) allowed for a more comprehensive and systematic evaluation. S. U. Han et al. (2020) studied the impact of the service quality and system quality of unmanned store kiosks on the intention of continued use, providing insights into successful operational strategies. Similarly, Alksasbeh et al. (2019) examined how information quality, system quality, and service quality influenced satisfaction and behavioral intentions in the context of mobile social network apps used in learning environments. In this study, based on previous research, reliability, usability, security, and interactivity are identified as key characteristics representing the quality of financial chatbot services as illustrated in Figure 4. These variables are crucial for understanding service quality dimensions in the financial chatbot context.

Category	Definition	Measurement Examples
System Quality	Desirable characteristics of an information system, such as reliability, accessibility, ease of use, response time, adequacy of computing resources, and security.	Reliability, ease of access, response time, user-friendliness, adequacy of computing resources, and security.
Information Quality	Desirable characteristics of the output of an information system, focusing on the content and value of the provided information.	Comprehensibility, accuracy, timeliness, reliability, usefulness, and expertise.
Service Quality	Support received by users from the information system organization and IT support staff, evaluated based on users' subjective perceptions of the services provided by system-related departments.	Responsiveness, convenience, tangibility, reliability, and interactivity.

Figure 4. Key variables identified from the IS-Success Model.

2.2.4. Post-Acceptance Model (PAM)

In the field of information systems, research has increasingly focused on post-adoption behaviors and continuous usage intentions beyond the initial adoption phase. Bhattacharjee (2001) proposed the Post-Acceptance Model by combining Oliver's (1980) expectation confirmation theory with the Technology Acceptance Model, identifying perceived usefulness, confirmation, and satisfaction as key factors affecting continuous usage intention. This model has become a representative framework for explaining success factors in information systems.

In domestic studies, the post-adoption model has been applied to various areas such as the CM channel of insurance companies (DeLone & McLean, 1992), OTT services (Pitt et al., 1995), and YouTube home training (Seddon, 1997). These studies found that service characteristics, information quality, content quality, and usage motivation significantly influence continuous usage intention through the mediating effects of confirmation, perceived usefulness, and satisfaction. For instance, Jeon and Yu (2023) found that service quality significantly impacts usage intention in finance and e-commerce, yet they overlooked the regulatory specifics of the financial sector. In contrast, S. J. Kim and Choi (2023) addressed this in the context of airline chatbots but did not explore long-term retention factors. Nguyen et al. (2021) bridged this gap by emphasizing trust and security as drivers of sustained use. While these studies address factors of chatbot continuance in finance,

this study integrates the Post-Acceptance Model to offer a more comprehensive analysis. Similarly, international studies have reported that confirmation, satisfaction, and perceived usefulness significantly affect continuous usage intention in contexts such as IPTV (S. U. Han et al., 2020), mobile services (Alksasbeh et al., 2019), group-buying websites (Oliver, 1993), and mobile messaging services (Kotler & Armstrong, 2004).

In this study, based on the Post-Acceptance Model, we investigate the factors that influence users' continuous usage intention of financial chatbots. This research framework provides a theoretical foundation for understanding the long-term adoption behavior of financial chatbot services.

3. Research Design

This study investigates the factors influencing the continuous usage intention of financial chatbot services in South Korea, utilizing variables grounded in established theories to address gaps in prior adoption-focused research. Key variables—social presence (SP), response accuracy (RA), assurance (AS), responsiveness (RE), reliability (RL), usability (US), security (SE), and Interactivity (IN)—are derived from frameworks like SERVQUAL, IS-Success, and the Post-Acceptance Model, supported by Nguyen et al. (2021), to assess service and system quality, reflecting South Korea's focus on chatbot retention in contrast to Europe's regulatory-driven approach prioritizing GDPR compliance (DeLone & McLean, 2003; Meyer-Waarden et al., 2020; J. T. Kim & Choi, 2022). These factors are mutually compatible, integrating SERVQUAL's service quality dimensions with the IS-Success Model's system quality dimensions to evaluate multi-dimensional influences on chatbot retention. The survey in this study was validated by three experts based on Parasuraman et al. (1988)'s SERVQUAL model. Trust is defined as the user's confidence in the chatbot's ability to deliver accurate and secure services, usability (US) refers to the ease of interacting with its interface, and security (SE) refers to the chatbot's ability to protect user data and system access (H. Y. Lee, 2023). This validation ensured the survey's appropriateness for assessing the quality of financial chatbot services. Potential confounding factors, such as user demographics, were not fully controlled due to sample constraints, noted as a limitation in Section 6.2.

3.1. Research Model

This study aims to examine the factors affecting continuous usage intention of financial chatbot services as shown in Figure 5. Key characteristics such as social presence, response accuracy, Assurance, and responsiveness were identified, along with system quality factors including reliability, usability, security, and interactivity. The Post-Acceptance Model is used to verify the impact of perceived usefulness, confirmation, and satisfaction on continuous usage intention. Furthermore, this study adopted partial least squares structural equation modeling (PLS-SEM) as the analytical method. As noted by Hair et al. (2014), PLS-SEM is particularly suitable for exploratory studies and small sample sizes ($n = 250$), making it an effective approach for analyzing complex relationships among variables in this context. Correlation analysis revealed that Usability did not significantly influence continuous usage intention ($t = -0.476$, $p = 0.634$). This may suggest that usability functions as a baseline expectation among financial chatbot users, likely perceived as a fundamental requirement rather than a direct driver of usage intention.

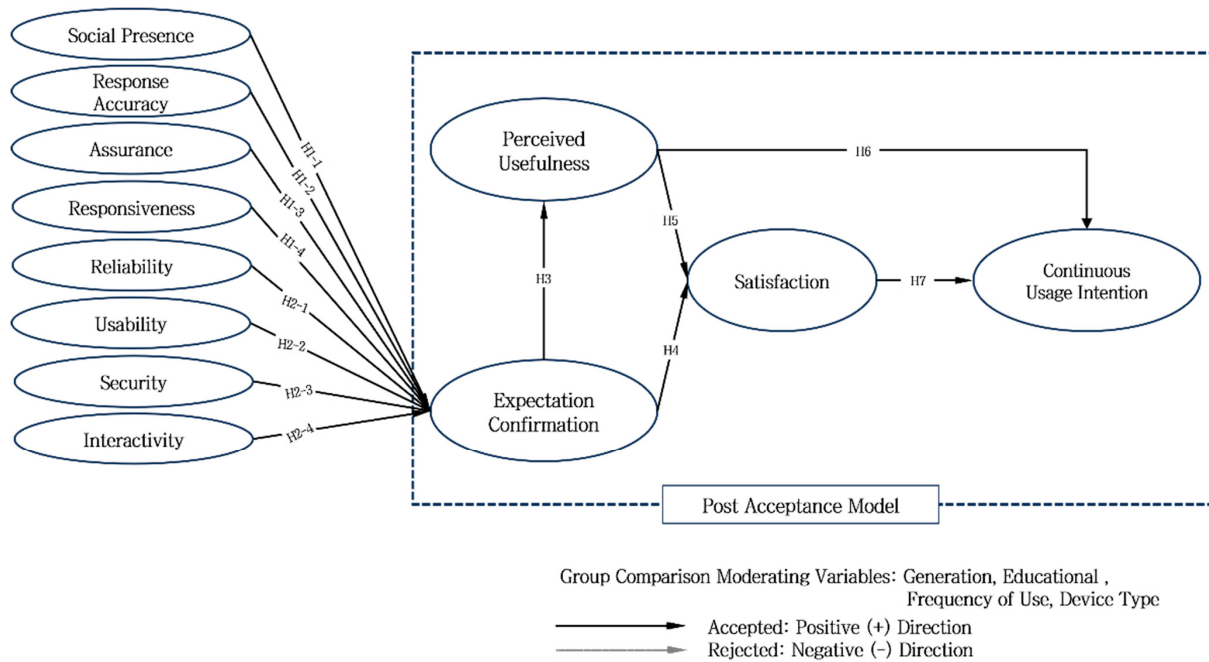


Figure 5. Research model.

3.2. Hypothesis Development

3.2.1. Relationship Between Financial Chatbot Service Characteristics and Expectation Confirmation

In financial chatbot services, social presence makes users perceive the chatbot as realistic, while response accuracy refers to the chatbot's ability to understand and process user requests correctly. Assurance provides trust in the chatbot's knowledge, competence, and safety, whereas responsiveness is expected to positively influence expectation confirmation through prompt service. Expectation confirmation assesses how well the service meets prior expectations and is crucial for consumer satisfaction and repurchase decisions (Oliver, 1980). Thus, this study formulates hypotheses on the relationship between financial chatbot characteristics and expectation confirmation.

H1. *The characteristics of financial chatbot services will have a positive effect on expectation confirmation.*

H1-1. *Social presence will have a positive effect on expectation confirmation.*

H1-2. *Response accuracy will have a positive effect on expectation confirmation.*

H1-3. *Assurance will have a positive effect on expectation confirmation.*

H1-4. *Responsiveness will have a positive effect on expectation confirmation.*

3.2.2. Relationship Between Information System Quality Characteristics and Expectation Confirmation

Reliability ensures consistent and accurate delivery of promised services, while usability helps users easily understand the information they need (Bailey & Pearson, 1983). Security guarantees system access and protects user information, and interactivity facilitates smooth communication between the service and the user, which is expected to positively influence expectation confirmation (Moon, 2010). Therefore, this study establishes hypotheses based on prior research regarding the relationship between information system quality and expectation confirmation.

H2. *Information system quality characteristics will have a positive effect on expectation confirmation.*

H2-1. *Reliability will have a positive effect on expectation confirmation.*

H2-2. *Usability will have a positive effect on expectation confirmation.*

H2-3. *Security will have a positive effect on expectation confirmation.*

H2-4. *Interactivity will have a positive effect on expectation confirmation.*

3.2.3. Relationship Between Expectation Confirmation and Perceived Usefulness

Expectation confirmation refers to the degree to which initial expectations align with the actual experience of using the service (Oliver, 1980). It is anticipated that expectation confirmation will positively influence the perceived usefulness of financial chatbot services. Therefore, based on prior research on expectation confirmation and perceived usefulness, this study establishes relevant hypotheses.

H3. *Expectation confirmation will have a positive effect on perceived usefulness.*

3.2.4. Relationship Between Expectation Confirmation and Satisfaction

Expectation confirmation represents the extent to which initial expectations are met during actual use of the service (J. H. Lee et al., 2018). It is expected that expectation confirmation will positively affect user satisfaction with financial chatbot services. Therefore, this study formulates hypotheses based on prior research regarding the relationship between expectation confirmation and satisfaction.

H4. *Expectation confirmation will have a positive effect on satisfaction.*

3.2.5. Relationship Between Perceived Usefulness and Satisfaction

Perceived usefulness refers to the extent to which users believe that using the service will enhance their performance or fulfill their needs (Yoon & Kim, 2006). It is anticipated that perceived usefulness will positively influence user satisfaction with financial chatbot services. Therefore, based on prior research on perceived usefulness and satisfaction, this study establishes relevant hypotheses.

H5. *Perceived usefulness will have a positive effect on satisfaction.*

3.2.6. Relationship Between Perceived Usefulness and Continuous Usage Intention

Perceived usefulness reflects the degree to which users believe the a service will improve their outcomes or fulfill their objectives (Yeo, 2002). It is expected that perceived usefulness will positively influence users' continuous usage intention. Therefore, based on prior research on perceived usefulness and continuous usage intention, this study formulates relevant hypotheses.

H6. *Perceived usefulness will have a positive effect on continuous usage intention.*

3.2.7. Relationship Between Satisfaction and Continuous Usage Intention

Satisfaction represents the overall level of contentment users experience from using a service (Yoo, 2021). It is expected that satisfaction will positively affect the continuous usage intention of financial chatbot services. Therefore, this study formulates hypotheses based on prior research regarding the relationship between satisfaction and continuous usage intention.

H7. *Satisfaction will have a positive effect on continuous usage intention.*

4. Research Results

4.1. Data Collection

Data collection for this study was conducted using SurveyMonkey from 3 February to 20 February 2024, targeting 250 users with experience using financial chatbot services in South Korea. Participants were randomly selected to ensure representativeness, contrasting with Europe's more regulated data collection approaches under GDPR. This sampling strategy aligns with South Korea's focus on operational efficiency amid branch reduction, though it limits control over confounding factors like user demographics, as noted in Section 6.2.

4.2. Demographic Analysis

Among the 250 respondents, 54.4% were male and 45.6% were female. The largest age group was 30–39 years old (25.2%), while the Millennial generation represented the highest proportion by generation (38.4%). The most frequently used financial institution was a bank (45.0%), with usage frequency of more than eight times (37.2%), and mobile devices were the most commonly used platform (71.6%). The results of the demographic characteristics analysis conducted through the survey are presented in Table 1.

Table 1. Demographic characteristics of the sample.

	Category	Frequency (n)	Percentage (%)	Group
Gender	Male	136	54.4	
	Female	114	45.6	
	Total	250	100	
Age	20–29 years	62	24.8	
	30–39 years	63	25.2	
	40–49 years	61	24.4	
	50–59 years	47	18.8	
	60 years or older	17	6.8	
	Total	250	100	
Generation	Generation Z (after 1995)	65	26	MZ Generation
	Millennials (1980–1994)	96	38.4	
	Generation X (1965–1979)	74	29.6	Older Generation
	Baby Boomers (1950–1964)	15	6	
	Total	250	100	
Financial Institution Usage	Bank	228	45	
	Securities	74	14.6	
	Insurance	58	11.4	
	Credit Card	123	24.3	
	Savings Bank	20	3.9	
	Other	4	0.8	
	Total	507	100	
Usage Frequency	1 time	4	1.6	1–3 times
	2–3 times	57	22.8	
	4–5 times	58	23.2	4 or more times
	6–7 times	38	15.2	
	8 or more times	93	37.2	
	Total	250	100	
Device Used	Mobile	179	71.6	Mobile PC
	PC	17	6.8	
	Both	54	21.6	
	Total	250	100	

4.3. Reliability and Validity Analysis

The statistical analysis was conducted under the assumption that the sample follows a normal distribution, which provides advantages in terms of efficient parameter estimation

and hypothesis testing (Hair et al., 2014). R was used for descriptive statistics and normality testing, with skewness and kurtosis as key metrics. Skewness measures the asymmetry of the distribution, while kurtosis assesses the flatness of the peak of the distribution. Absolute values exceeding ± 1.96 for skewness and ± 2 for kurtosis are considered indicative of an extreme distribution (Gefen & Straub, 2005). As shown in Table 2, the skewness and kurtosis of all variables are within these acceptable ranges, indicating no significant issues with normality. Specifically, the skewness values range from -0.874 to 0.034 , and the kurtosis values range from -0.528 to 1.343 , all falling within the acceptable limits of ± 1.96 for skewness and ± 2 for kurtosis. This confirms that the data meet the normality assumption required for further statistical analyses.

Table 2. Descriptive analysis of observed variables.

Latent Variable	Observed Variable	Mean	Standard Deviation	Skewness	Kurtosis
Social Presence	SP1	4.328	1.200	−0.427	0.678
	SP2	4.104	1.377	−0.003	−0.370
	SP3	3.804	1.478	0.034	−0.523
	SP4	4.040	1.446	−0.284	−0.442
Response Accuracy	RA1	4.468	1.251	−0.492	0.078
	RA2	4.456	1.297	−0.403	−0.150
	RA3	4.396	1.355	−0.413	−0.022
Assurance	AS1	4.408	1.373	−0.415	−0.266
	AS2	4.784	1.349	−0.640	0.328
	AS3	4.284	1.428	−0.267	−0.382
	AS4	4.424	1.339	−0.283	−0.157
	AS5	4.336	1.269	−0.154	−0.155
Responsiveness	RE1	4.868	1.182	−0.601	0.502
	RE2	5.288	1.223	−0.666	0.441
	RE3	4.524	1.292	−0.559	0.195
	RE4	4.380	1.338	−0.464	−0.101
	RE5	4.432	1.351	−0.328	−0.265
Reliability	RL1	4.760	1.246	−0.458	0.392
	RL2	4.816	1.197	−0.469	0.251
	RL3	4.776	1.210	−0.608	0.561
	RL4	4.884	1.149	−0.548	0.808
Usability	US1	5.096	1.211	−0.874	1.343
	US2	5.012	1.326	−0.660	0.134
	US3	5.364	1.146	−0.470	−0.040
	US4	5.100	1.232	−0.794	0.988
Security	SE1	4.732	1.102	−0.067	0.050
	SE2	4.720	1.115	−0.195	0.439
	SE3	4.804	1.187	−0.336	0.391
	SE4	4.708	1.204	−0.252	0.372
Interactivity	IN1	4.444	1.312	−0.452	0.115
	IN2	4.452	1.390	−0.384	−0.117
	IN3	4.304	1.442	−0.339	−0.406
	IN4	4.480	1.323	−0.408	0.288
Expectation Confirmation	EC1	4.224	1.409	−0.331	−0.040
	EC2	4.204	1.494	−0.336	−0.390
	EC3	4.104	1.503	−0.226	−0.497
	EC4	4.444	1.363	−0.304	0.012
Perceived Usefulness	PU1	4.660	1.364	−0.659	0.366
	PU2	4.592	1.396	−0.440	−0.156
	PU3	4.576	1.403	−0.525	0.205
	PU4	4.488	1.396	−0.337	−0.214

Table 2. Cont.

Latent Variable	Observed Variable	Mean	Standard Deviation	Skewness	Kurtosis
Satisfaction	SA1	4.600	1.410	−0.615	0.182
	SA2	4.448	1.452	−0.619	−0.114
	SA3	4.416	1.531	−0.430	−0.329
Continuous Usage Intention	CI1	4.560	1.386	−0.507	0.043
	CI2	4.400	1.519	−0.412	−0.317
	CI3	4.132	1.612	−0.420	−0.528
	CI4	4.424	1.539	−0.473	−0.322

Table 3 presents the results of the internal consistency reliability assessment. The Cronbach's α coefficients for the latent variables exceeded the threshold of 0.7, and the composite reliability (CR, DG. ρ) values also surpassed 0.7 (S. J. Lee, 2023). Additionally, the eigenvalue for each latent variable met the criterion of being greater than or equal to 1.0 (S. J. Lee, 2023). Thus, the internal consistency reliability and composite reliability of all latent variables were well above the required thresholds, ensuring the internal reliability of the measurement indicators.

Table 3. Assessment of internal consistency reliability.

Latent Variable	MVs	C.alpha	DG.rho	Eig.value
Social Presence	4	0.881	0.918	2.951
Response Accuracy	3	0.922	0.950	2.594
Assurance	5	0.909	0.932	3.674
Responsiveness	5	0.902	0.928	3.614
Reliability	4	0.895	0.927	3.044
Usability	4	0.874	0.914	2.907
Security	4	0.923	0.945	3.248
Interactivity	4	0.912	0.938	3.167
Expectation Confirmation	4	0.940	0.957	3.390
Perceived Usefulness	4	0.941	0.958	3.399
Satisfaction	3	0.933	0.957	2.644
Continuous Usage Intention	4	0.951	0.965	3.489

The validity evaluation of the PLS-SEM structural equation model was conducted by assessing discriminant validity and convergent validity. Discriminant validity was evaluated through the square root of the average variance extracted (AVE) and the cross-loading criteria. If the square root of the AVE for each variable is greater than the correlation coefficients between that latent variable and other latent variables, the model is considered to have achieved discriminant validity (Gefen & Straub, 2005). As shown in Table 4, the diagonal values of the AVE square root were higher than the correlation coefficients with other latent variables, confirming the discriminant validity of the model.

Correlation analysis results showed that most variables were significantly correlated. Social presence exhibited a high correlation with interactivity ($r = 0.79$) and assurance ($r = 0.78$). Response accuracy was strongly correlated with assurance ($r = 0.84$) and expectation confirmation ($r = 0.83$). Responsiveness showed a high correlation with reliability ($r = 0.85$) and interactivity ($r = 0.84$). Perceived usefulness was strongly correlated with expectation confirmation ($r = 0.86$) and assurance ($r = 0.85$). Satisfaction exhibited high correlations with perceived usefulness ($r = 0.90$), assurance ($r = 0.89$), and expectation confirmation ($r = 0.87$). Expectation confirmation showed a strong correlation with continuous usage intention ($r = 0.89$), while continuous usage intention was highly correlated with satisfaction ($r = 0.91$), expectation confirmation ($r = 0.89$), and perceived usefulness

($r = 0.89$). The results of the correlation analysis are presented in Figure 6. This heatmap uses a grayscale gradient to represent correlation coefficients, with darker shades indicating stronger correlations (closer to 1). Values are displayed in each cell for clarity.

Table 4. Convergent and discriminant validity evaluation results.

Vars.	SP	RA	AS	RE	RL	US	SE	IN	EC	PU	SA	CI	√AVE
SP	0.737												0.859
RA	0.729	0.865											0.930
AS	0.777	0.839	0.735										0.857
RE	0.690	0.804	0.851	0.722									0.850
RL	0.631	0.801	0.822	0.846	0.761								0.872
US	0.538	0.654	0.673	0.726	0.695	0.726							0.852
SE	0.554	0.584	0.641	0.655	0.693	0.601	0.812						0.901
IN	0.788	0.772	0.849	0.837	0.760	0.677	0.679	0.791					0.890
EC	0.772	0.832	0.868	0.795	0.759	0.627	0.579	0.843	0.847				0.921
PU	0.710	0.772	0.849	0.792	0.769	0.662	0.629	0.839	0.858	0.850			0.922
SA	0.737	0.807	0.888	0.816	0.780	0.691	0.585	0.847	0.870	0.896	0.881		0.939
CI	0.730	0.800	0.868	0.777	0.759	0.655	0.587	0.811	0.889	0.888	0.907	0.872	0.934

SP: social presence, RA: response accuracy, AS: assurance, RE: responsiveness, RL: reliability, US: usability, SE: security, IN: interactivity, EC: expectation confirmation, PU: perceived usefulness, SA: satisfaction, CI: continuous usage intention. Note: Gray background indicates the square root of the average variance extracted ($\sqrt{\text{AVE}}$).

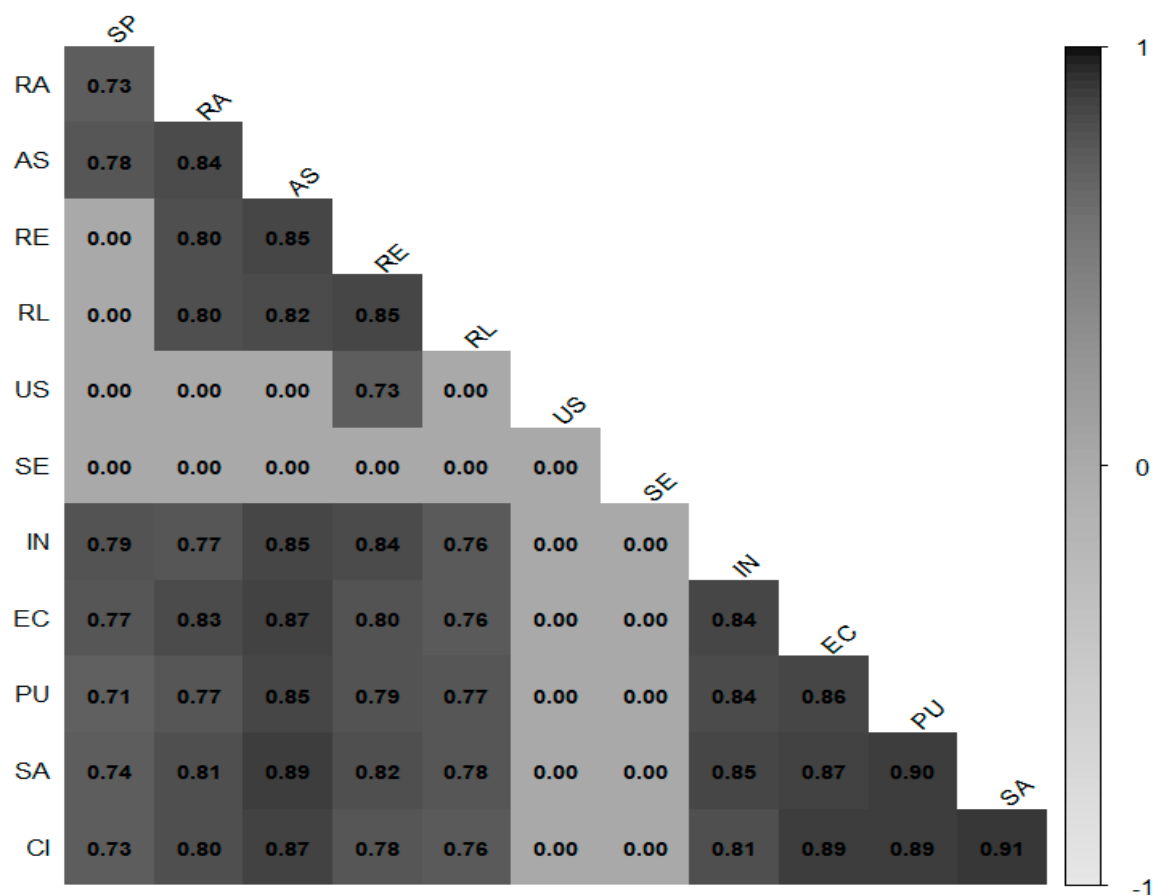


Figure 6. Significant Correlations ($|r| > 0.7$). SP: social presence, RA: response accuracy, AS: assurance, RE: responsiveness, RL: reliability, US: usability, SE: security, IN: interactivity, EC: expectation confirmation, PU: perceived usefulness, SA: satisfaction, CI: continuous usage intention.

To enhance readability in black-and-white printing, Figure 6 has been simplified to highlight only the significant correlations ($|r| > 0.7$) in a heatmap format, using a grayscale gradient to indicate the strength of relationships. Correlation values are directly displayed

in each cell to ensure clarity. Responsiveness (RE) shows strong correlations with reliability (RL, $r = 0.85$) and interactivity (IN, $r = 0.84$) in the heatmap (Figure 6), but its correlations with satisfaction (SA, $r = 0.82$) and continuous usage intention (CI, $r = 0.78$) are relatively weaker compared to response accuracy (RA) with expectation confirmation (EC, $r = 0.83$), suggesting that users may value accuracy over speed in driving satisfaction and retention.

4.4. Path Analysis Results

In the path analysis, path coefficients were evaluated for statistical significance using a non-parametric bootstrapping method with the PLSPM Package in R (2000 iterations), employing structural equation modeling (SEM) and determining significance at the 5% level ($t\text{-value} > 1.96$) (S. J. Lee, 2023; Oh et al., 2019). The critical t -value for a two-tailed test is generally 1.96, which corresponds to a significance level of 5% (S. J. Lee, 2023). The results of the path analysis are presented in Table 5.

Table 5. Path analysis results.

Hypothesis		Path		Estimate	Std.Error	t-Value	p-Value		Result
H1	H1-1	Social Presence		0.106	0.034	3.137	0.002	**	Supported
	H1-2	Response Accuracy		0.265	0.039	6.735	0.000	***	Supported
	H1-3	Assurance		0.330	0.048	6.867	0.000	***	Supported
	H1-4	Responsiveness	→	Expectation	−0.006	0.046	−0.134	0.894	
H2	H2-1	Reliability		0.039	0.042	0.921	0.357		Rejected
	H2-2	Usability		−0.014	0.029	−0.476	0.634		Rejected
	H2-3	Security		−0.068	0.028	−2.396	0.017	*	Supported
	H2-4	Interactivity		0.306	0.044	6.903	0.000	***	Supported
H3	Expectation Confirmation	→	Perceived Usefulness	0.858	0.023	37.264	0.000	***	Supported
H4	Expectation Confirmation	→	Satisfaction	0.384	0.035	11.076	0.000	***	Supported
H5	Perceived Usefulness			0.567	0.035	16.364	0.000	***	Supported
H6	Perceived Usefulness	→	Continuous Usage Intention	0.383	0.039	9.824	0.000	***	Supported
H7	Satisfaction			0.564	0.039	14.473	0.000	***	Supported

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The path analysis results, considering the critical value ($t\text{-value} = 1.96$) at the 5% significance level, are as follows: Skewness, kurtosis (± 1.96 , ± 2), and VIF (< 3.0) confirm normality and no multicollinearity, ensuring PLS-SEM validity (model fit validated). For the path analysis between financial chatbot service characteristics and expectation confirmation, social presence ($t = 3.137$, $p = 0.002$), response accuracy ($t = 6.735$, $p = 0.000$), and assurance ($t = 6.867$, $p = 0.000$) were found to have a positive effect on expectation confirmation, while responsiveness ($t = -0.134$, $p = 0.894$) was rejected, indicating no significant impact. Responsiveness (RE) has no significant impact on expectation confirmation (EC) ($t = -0.134$, $p = 0.894$), suggesting that users may prioritize accuracy over speed in financial chatbot interactions.

In the path analysis between information system quality characteristics and expectation confirmation, interactivity ($t = 6.903$, $p = 0.000$) positively affected expectation confirmation, while security ($t = -2.396$, $p = 0.017$) negatively affected expectation confirmation. Reliability ($t = 0.921$, $p = 0.357$) and usability ($t = -0.476$, $p = 0.634$) showed no significant effect.

For the path analysis between expectation confirmation and perceived usefulness, expectation confirmation ($t = 37.264$, $p = 0.000$) positively influenced perceived usefulness. In the analysis of expectation confirmation, perceived usefulness, and satisfaction, expectation confirmation ($t = 11.076$, $p = 0.000$) and perceived usefulness ($t = 16.364$, $p = 0.000$) both positively affected satisfaction, with perceived usefulness showing a stronger effect. In the

path analysis between perceived usefulness, satisfaction, and continuous usage intention, perceived usefulness ($t = 9.824, p = 0.000$) and satisfaction ($t = 14.473, p = 0.000$) both positively influenced continuous usage intention, with satisfaction exhibiting a stronger effect. Overall, interactivity had the greatest impact on expectation confirmation, followed by assurance, response accuracy, and social presence, in that order. The research model with these results is shown in Figure 7.

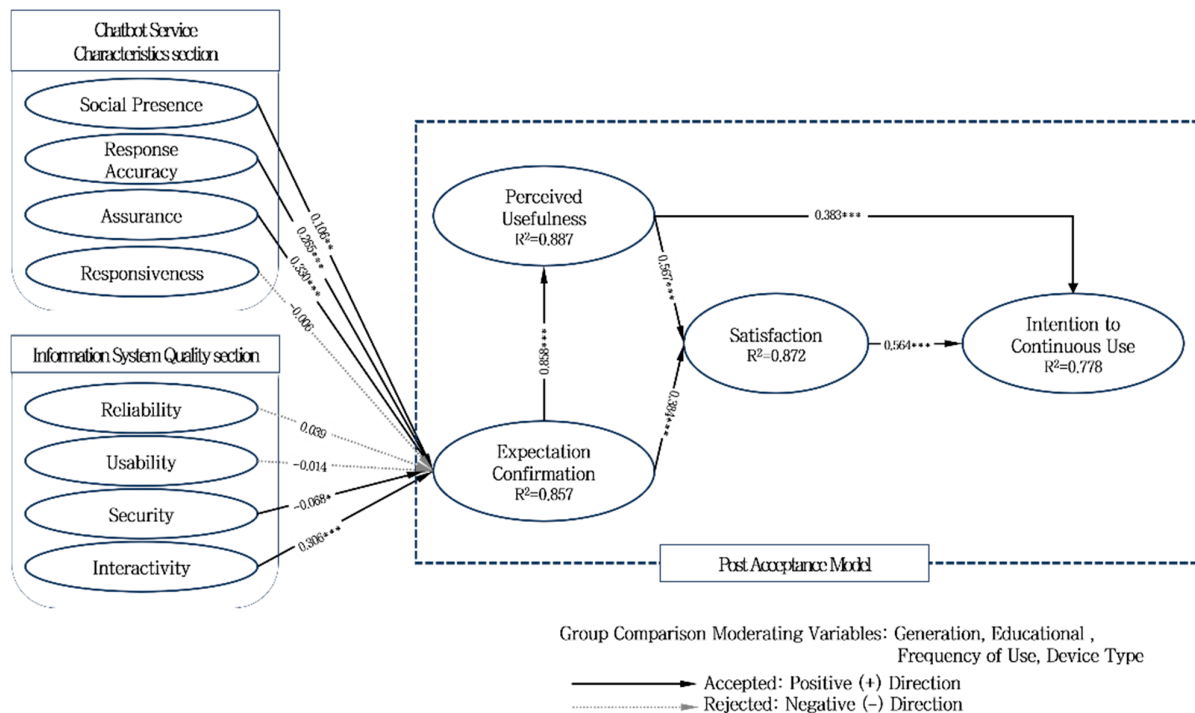


Figure 7. Path analysis results. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5. Discussion

The correlation analysis revealed significant relationships among the variables, with continuous usage intention showing strong positive correlations with satisfaction ($r = 0.91, p < 0.01$ **), expectation confirmation ($r = 0.89, p < 0.01$ **), and perceived usefulness ($r = 0.89, p < 0.01$ **), while satisfaction correlated highly with perceived usefulness ($r = 0.90, p < 0.01$ **) and assurance ($r = 0.89, p < 0.01$ **). These findings align with prior studies, such as [Bhattacharjee \(2001\)](#), which highlight satisfaction as a critical driver of continuous usage intention in technology adoption contexts.

Similarly, [J. T. Kim and Choi \(2022\)](#) found that anthropomorphic characteristics of AI chatbots enhance user satisfaction and loyalty ([Meyer-Waarden et al., 2020](#)), supporting the pivotal role of satisfaction in user retention. The strong association between perceived usefulness and satisfaction supports the Technology Acceptance Model (TAM) framework ([Davis, 1989](#)), indicating that perceived utility enhances user satisfaction, a finding consistent with [D. H. Kim and Lee \(2023\)](#), who noted the importance of perceived usefulness in AI-driven financial services.

Moreover, the correlation between expectation confirmation and continuance intention underscores the importance of meeting user expectations to enhance retention. These results could be further amplified by integrating generative AI technologies, such as ChatGPT (GPT-4o), which enhance social presence and response accuracy—key characteristics identified in this study (see Figures 2 and 3). For instance, [Yu and Min \(2023\)](#) suggested that ChatGPT's natural and context-aware responses improve user satisfaction, aligning with

social presence theory (Oghuma et al., 2016), which emphasizes the role of social presence in fostering engagement.

Additionally, J. T. Kim and Choi (2022) noted that human-like features in AI chatbots, which generative AI can enhance, strengthen user satisfaction, potentially increasing continuance intention by making interactions more reliable and trustworthy. From a practical perspective, financial institutions should focus on improving user satisfaction and perceived usefulness through reliable and responsive chatbot services while adopting generative AI to enhance social presence and response accuracy, thereby further promoting sustained usage.

6. Conclusions

6.1. Significance and Implications of the Study

Non-face-to-face transactions and branch reductions post-COVID-19 have increased the importance of financial chatbot services, with South Korea's operational efficiency driving retention efforts, unlike Europe's GDPR-focused trust-building approach. Interactivity and assurance were identified as key drivers of continuous usage intention. Notably, frequent users showed heightened sensitivity to security due to data privacy concerns, exacerbating trust issues and lowering expectation confirmation. Advances like ChatGPT could further boost interactivity, offering future potential for South Korea's retention goals, contrasting with Europe's regulatory constraints.

6.1.1. Theoretical Implications

This study holds academic significance as it addresses the limitations of previous studies and provides a more comprehensive understanding of financial chatbot services. Unlike previous research that focused primarily on individual analyses of chatbot service quality or acceptance intention, this study expands the research scope through the following differentiated approaches:

First, the service quality measurement model was used to derive four key characteristics of financial institution chatbot services (social presence, response accuracy, assurance, and responsiveness) and to build a comprehensive analytical framework by including four information system quality characteristics (reliability, usability, security, and interactivity).

Second, the Post-Acceptance Model was applied to systematically analyze the complex interrelationships between factors affecting the continuous usage intention of financial institution chatbot services. This novel approach, which has not been attempted in previous studies, contributes to understanding the long-term success factors of chatbot services.

Through these academic contributions, this study enhances the understanding of consumer behavior in the use of financial institution chatbot services and contributes to the advancement of the related research field by applying the post-acceptance model to the financial industry.

6.1.2. Practical Implications

The practical implications of this study are as follows:

First, assurance and social presence significantly enhance expectation confirmation, particularly among users with over four interactions and those with at least a bachelor's degree, suggesting financial institutions should adopt strategies promoting repeated use and trust-building.

Second, among information system quality characteristics, interactivity was found to be the most important factor affecting expectation confirmation. Notably, frequent users expressed concerns about security. On the other hand, reliability and usability did not have significant effects, suggesting that these are perceived as basic requirements.

Therefore, financial institutions should focus on enhancing interactivity and improving trust in security while providing differentiated personalized services.

Third, perceived usefulness, expectation confirmation, satisfaction, and continuous usage intention were all found to have positive correlations. Notably, expectation confirmation was higher among mobile users, and satisfaction was greater among older generations compared to the MZ generation. These results suggest the need for differentiated strategies that consider generational characteristics and usage environments.

Financial institutions should improve user experience through mobile optimization, customized UI/UX design for each generation, and real-time feedback features to promote continuous use.

6.2. Limitations and Future Study

This study provides valuable academic and practical insights through empirical analysis but is subject to several limitations requiring future exploration, particularly in South Korea's retention-driven context versus Europe's regulatory framework.

First, the sample's demographic diversity was limited, potentially skewing results toward frequent users, a bias less prevalent in Europe's broader compliance-focused studies. Future studies should enhance generalizability by comparing demographic groups (e.g., gender, age, income, and education) or securing a more diverse sample.

Second, this study was conducted in a transitional period when generative AI technology was not yet widely adopted in financial institutions. Future research should analyze the actual changes in financial institution chatbot services and the relationships between variables after the adoption of generative AI.

Additionally, reliance on self-reported survey responses may introduce response bias, potentially limiting the objectivity of results; experimental designs could address this by analyzing user responses in real chatbot usage environments. Furthermore, cross-national comparisons could analyze regional differences in chatbot retention; longitudinal studies could explore long-term user behavior changes, and qualitative insights could examine emotional and cultural factors influencing sustained chatbot use.

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Institutional Review Board Statement: This research involved collecting data via a questionnaire survey of participants, in line with Article 1 of the Bioethics and Safety Act of Korea: "The Intention to Continuous Use of Chatbot Services in Financial Institutions", Master's Thesis, Soongsil University, Seoul, Korea, 2004". This research was adapted and developed from a portion of Ms. Y. S. Choi's master's thesis. As a result, it is eligible for independent evaluation under the supervision of a thesis advisor, in accordance with our university's exception rule to IRB Screening.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The raw data supporting the conclusions of this study will be made available by the corresponding author upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

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