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Navigating Behavioural Barriers to Fintech Chatbot Adoption: An Extended Innovation Resistance Theory Approach

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Abstract

The study explores the multifaceted dimensions of user resistance through the lens of the Extended Innovation Resistance Theory (IRT), providing insight into functional, psychological and behavioural inhibitors that prevent users from integrating fintech chatbot functionality into their financial management practices. This study employed a quantitative approach and conducted PLS-SEM to analyse the data collected from 286 fintech users. Findings suggest that behavioural inhibitors and IRT variables, except image barrier, play a critical role in preventing users from adopting fintech chatbots. This study emphasises the need to address these behavioural complexities to foster a more conducive environment for the integration of fintech chatbot technology into the financial services industry. A significant contribution of this research is that it introduces a behavioural dimension to the IRT to explore factors affecting the adoption of fintech chatbots, thus contributing to the existing literature on the user adoption and resistance of technology.

***Keywords*:** Fintech Chatbots, User Resistance, Innovation Resistance Theory, Inertia, Procrastination

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Introduction

The relentless integration of financial technology (fintech) solutions has caused a significant transformation in the financial services industry in recent years. Among these developments, chatbots have become increasingly popular as a critical component in reshaping customer engagement and service delivery (Huang & Lee, 2022). A fintech chatbot is a virtual assistant powered by artificial intelligence (AI) that provides personalised interactions and transactions in the financial services sector (Huang & Lee, 2022). They enhance customer service and accessibility by providing real-time guidance, account information, and seamless financial transactions using natural language processing. Chatbots have shown promise in streamlining financial interactions and improving user experiences, however, their seamless integration has been hindered by user resistance (Huang et al., 2024; Kwangsawad & Jattamart, 2022).

Despite their willingness to embrace fintech for other financial services, individual users may be reluctant to embrace a fintech chatbot for various reasons (Huang et al., 2024; Kwangsawad & Jattamart, 2022). The perceived complexity associated with the use of chatbot features is one of the most critical factors. Users may find the interface difficult to navigate, resulting in a reluctance to engage fully with the technology (Kwangsawad & Jattamart, 2022). Furthermore, users may be cautious about using chatbots due to concerns regarding their trustworthiness and security. Users who perceive potential risks, such as data breaches or fraudulent activities, may choose traditional methods perceived as safer, for managing their finances. Furthermore, users may prefer human interaction for more complex financial queries, believing that human advisors are more reliable and capable of understanding complex financial requirements (Huang et al., 2024). Additionally, a lack of awareness of the capabilities and benefits of chatbots within the fintech landscape may result in a reluctance to fully utilise their capabilities.

To understand the underlying factors that influence the adoption of chatbots for financial services, it is imperative to understand the nuanced dynamics of user resistance. Although researchers have made progress in understanding non-adoption within the broader context of fintech (Rabaa'i et al., 2024; Talwar et al., 2021), a critical research gap remains regarding the barriers to the adoption of fintech chatbots. In order to understand the factors of user resistance to fintech chatbots, it is essential to examine the distinctive barriers associated with fintech chatbots. The barriers to technology adoption stem from a multifaceted interplay between users' psychological and behavioural attributes and challenges originating from the side of technology providers (Mercenier & Voyvoda, 2021; Rad et al., 2017). These attributes and challenges also should be addressed. Addressing this gap will contribute significantly to the existing body of knowledge on fintech adoption, providing insights that can shape interventions to enhance user acceptance of chatbots in the financial services domain.

By emphasising functional and psychological barriers, Innovation Resistance Theory (IRT) has provided researchers with a comprehensive framework for analysing the various barriers to adopting new technologies (Ram & Sheth, 1989). Accordingly, the IRT framework can emphasise functional barriers, such as usage, value, and risk barriers, resulting from consumers' perceptions of the changes brought about by the adoption of innovations (Ram & Sheth, 1989). Moreover, psychological barriers such as traditional and image barriers have been recognised as crucial components resulting from perceived contradictions to consumers' prior beliefs (Ram & Sheth, 1989). The IRT has been extensively used to examine technological adoption barriers, and its capability to understand the interplay between user psychological attributes and functional challenges is well recognized (Kumari et al., 2024; Ghosh, 2022). However, a notable gap exists when it comes to empirical research incorporating behavioural barriers within the framework of IRT, such as inertia and procrastination. These behavioural dimensions can illuminate users' cognitive processes and decision-making tendencies that influence their resistance to change and their delay in adopting innovative technologies (Malodia et al., 2022). Integrating procrastination and inertia into the model enhances the real-world applicability of IRT, making it reflective of the diverse nature of users' reactions to innovation.

The aim of the study was to gain insight into the consumer barriers impeding the seamless integration of chatbot technology into financial services by examining users' functional, psychological and behavioural barriers. In this paper, we apply an Extended Innovation Resistance Theory (IRT) approach to examine the underlying factors that shape user resistance (i.e., intention not to adopt) in the context of fintech chatbots. The objective of this analysis is to propose effective strategies for reducing user resistance and fostering an environment conducive to the widespread adoption of chatbots in the financial industry.

Literature Review and Theoretical Background

Fintech Chatbot and Non-adoption

The rapid evolution of fintech has transformed the global financial services sector, providing innovative solutions that improve efficiency and user experience

(Belanche et al., 2019; Diéguez et al., 2023). The factors around the adoption of chatbots have become a noteworthy focal point as users increasingly embrace fintech (Dekkal et al., 2023; Priya & Sharma, 2023). Despite consumer adoption of fintech, a paradoxical phenomenon exists: individual users refuse to adopt fintech chatbots while engaging with overarching fintech platforms. This resistance originates from a variety of issues, including trust and security concerns, a perceived lack of value, user experience challenges, and established habits (Dwivedi et al., 2023; Kwangsawad & Jattamart, 2022). While previous work has thoroughly examined the adoption factors (Cai et al., 2022; Chen et al., 2023; Upadhyay & Kamble, 2023), there is still a gap in understanding the factors affecting resistance to fintech chatbot adoption.

Extant studies have examined the individual users' innovation resistance in various contexts like mobile payment (Khanra et al., 2021), e-health services (Ray et al., 2022), mobile ticketing applications (Chen et al., 2022), and service robots (Lee & Kim, 2022). However, consumers' resistance to adopting fintech chatbots was explored very little. The current conversation on innovation resistance focuses mostly on technological and functional factors (Cham et al., 2021; Prakash & Das, 2022), ignoring the delicate interaction of human behaviour, emotions, and habits during the adoption process. There is a need to fill this gap by looking into the psychological and behavioural factors that influence users' decision-making, providing a more comprehensive knowledge of the dynamics of fintech chatbot adoption. This holistic approach would help to overcome barriers and develop broader acceptance of fintech chatbots in the ever-changing financial technology landscape.

Innovation Resistance Theory

IRT, proposed by Ram and Sheth in 1989, has emerged as a foundational framework for comprehending consumer resistance and behaviour towards innovation adoption. This theory posits that resistance-oriented behaviour emerges from a rational decision-making framework. It stems from assessing the potential disruption that new technologies may introduce to the existing system, prompting a deviation from current practices (Ghosh, 2022). In addition to other theoretical frameworks, IRT provides a comprehensive examination of consumer resistance to innovation (Prakash & Das, 2022). As opposed to diffusion of innovation and user acceptance models, IRT focuses specifically on resistance, thus making it suitable for examining the nuanced dynamics of fintech non-adoption and user behaviour in the financial services industry (Rabaa'i et al., 2024; Nel & Boshoff, 2022). IRT introduces a dual-barrier model, categorising resistance into functional and psychological barriers. The conflict arising from an innovation's practical aspects, such as usage, value, and risk, is linked to functional barriers. Tradition and image are two psychological barriers contributing to conflicts between an innovation and traditional beliefs and norms (Ram & Sheth, 1989). IRT has been successfully employed in studies on technological innovations (Ghosh, 2022), internet innovations (Laukkanen, 2016), healthcare technology innovations (Kumari et al., 2024), and various service innovations (Talwar et al., 2021). As a result of this widespread application, the theory exhibits adaptability and efficacy in explaining resistance across a wide range of contexts. As previously noted, in the context of fintech, there is a notable need to investigate why users are not adopting chatbots. IRT's focus on functional barriers (e.g., usage, value, and risk) aligns with the complexities of integrating chatbots into existing financial service practices. The potential disruptions to users' habits and the perceived risks associated with conducting financial transactions through chatbots make IRT particularly relevant.

Additionally, extending the IRT to include inertia (Dwivedi et al., 2023; Kim & Park, 2023) and procrastination (Alblwi et al., 2021; Malodia et al., 2022) in fintech chatbot non-adoption recognises crucial behavioural dimensions alongside the functional and psychological barriers. This enhancement captures a more holistic understanding of user resistance, acknowledging the intricate nature of decision-making. By incorporating inertia and procrastination, the theoretical framework gains depth, offering a nuanced perspective on factors shaping adoption. This extension provides a comprehensive foundation for research and practical applications in the evolving landscape of fintech.

Hypothesis Development

In this section, hypotheses are developed at the dimensional level, using the different dimensions of functional barriers (usage, value and risk), psychological barriers (traditional and image) and the newly introduced behavioural barriers (procrastination and inertia).

Usage Barrier

Usage barriers refer to obstacles that arise due to potential changes, particularly when adopting innovations in comparison to existing systems (Ram & Sheth, 1989). In our study context, usage barriers, which represent users' perceived difficulty and complexity in integrating fintech chatbots into their financial services interactions, may positively influence their non-adoption intentions. If users encounter challenges in understanding and integrating chatbots within their existing workflows, they may be more inclined to refrain from adopting these technological solutions (Huang et al., 2024). Studies have shown that users' resistance to change and their apprehension about the complexity of technology can significantly influence their non-adoption intentions (Chu, 2023; Lee & Kim, 2022). Moreover, studies have indicated that users are more likely to express a stronger reluctance to adopt chatbots when they perceive integration as disruptive or challenging (Kwangsawad & Jattamart, 2022). Based on these insights, the following hypothesis is proposed:

H_1: The usage barrier is positively associated with the non-adoption intention of the fintech chatbot.

Value Barrier

The value barrier necessitates that innovations provide better performance in relation to cost compared to existing alternatives for consumers to modify their behaviour (Laukkanen, 2016). The value barrier is a critical factor influencing users' perceptions of the advantages and benefits provided by fintech chatbots in comparison to traditional methods of providing financial services. The presence of this barrier may positively affect the non-adoption intent of users, causing them to doubt the tangible value proposition of integrating chatbot technology into their financial services interactions. It has been shown that users' concerns regarding the cost-effectiveness and value propositions of chatbot technology play a critical role in determining their non-adoption intentions (Gatzioufa & Saprikis, 2022) Unless an innovation offers greater value than current products, customers lack the incentive to make a change (Ram & Sheth, 1989). Further, research has revealed that users' assessments of the relative benefits of chatbots over existing service methods have a significant impact on their willingness to adopt innovative financial technologies (Almahameed & Gené-Albesa, 2023). In view of these insights, the following hypothesis is proposed:

H_2: The value barrier is positively associated with the non-adoption intention of the fintech chatbot.

Risk Barrier

The risk barrier pertains to the level of inherent risk associated with innovations, encompassing financial, psychological, physical, or social risks (Laukkanen, 2016). A user's perception of various risks associated with the integration of fintech chatbots into their financial service interactions may positively influence their non-adoption intentions. If users perceive chatbots as potentially posing risks, such as data security, financial instability, functional inadequacies, or social repercussions, they may be more inclined to refrain from implementing these technological solutions (Mehrolia et al., 2023). Researchers have found that users' risk perceptions have a significant impact on their decision-making process, suggesting that increased risk awareness may lead to greater reluctance or resistance to adopting chatbots (Bouhia et al., 2022). In addition, studies indicate that trust-building measures, robust data security protocols, and transparent communication strategies play an essential role in reducing users' perceived risks and fostering a more favourable environment for the adoption of fintech chatbots within the financial services industry (Huang & Lee, 2022). Based on these insights, the following hypothesis is proposed:

H_3: The risk barrier is positively associated with the non-adoption intention of the fintech chatbot.

Traditional Barrier

Tradition barriers encompass the challenges presented by any innovation when it introduces changes to a user's existing routine, culture, and behaviour (Ram & Sheth, 1989). In the field of technological adoption, research has highlighted the challenges associated with behaviour change and the effects of traditional barriers on users' hesitance to adopt new technologies (Chen et al., 2022; Kaur et al., 2020). Traditional barriers to fintech chatbot adoption may influence users' non-adoption intentions significantly. The resistance to altering established routines and habits that are attributed to traditional barriers may play a significant role in their unwillingness to adopt new technology (Bouhia et al., 2022; Ray et al., 2020). As a consequence of these findings, this study proposes that users are more likely to demonstrate non-adoption intentions in regards to fintech chatbot implementation due to perceived resistance to altering daily routines and habits.

H_4: The traditional barrier is positively associated with the non-adoption intention of the fintech chatbot.

Image Barrier

Image barrier refers to the impediments to adopting innovations caused by unfavourable associations linked to factors such as product category, country of origin, or brand, as users may resist embracing changes due to negative perceptions (Laukkanen, 2016; Ram & Sheth, 1989). In the context of fintech adoption, image barriers could play a significant role in influencing users' perceptions of fintech chatbots' credibility and reliability. If users perceive this barrier positively, it may lead to their non-adoption intentions being positively influenced, causing them to question the trustworthiness and effectiveness of integrating technology into their work routines (Musyaffi et al., 2022). Researchers have demonstrated how perceptions of users and their tendency to form stereotypes play a critical role in influencing their readiness to embrace new technologies (Ray et al., 2020). In addition, studies emphasise the importance of proactive branding initiatives, transparent communication strategies, and trust-building measures to counter negative perceptions and create a conducive environment for fintech chatbots to be integrated into the financial services industry (Dekkal et al., 2023) Building on these insights, the following hypothesis is postulated:

H_5: The image barrier is positively associated with the non-adoption intention of the fintech chatbot.

Procrastination

Procrastination in the context of technology adoption is the act of postponing the adoption or implementation of new technologies, where individuals delay making decisions regarding the integration of innovative tools or systems (Alblwi et al., 2021). In the context of fintech chatbots, procrastination may have a positive impact on the non-adoption intention. Procrastination is characterised as the tendency to delay or defer decisions regarding the adoption of new technologies (Malodia et al., 2022). The users may develop a stronger intention to refrain from adopting these technological solutions when they exhibit procrastination tendencies, such as avoiding or delaying the incorporation of bots into their financial service interactions (Malodia et al., 2022). Research findings demonstrate that procrastination behaviours significantly impact users' decision-making processes, emphasising how the tendency to delay or postpone actions can impede the adoption of innovative solutions (Andersson, 2016). Furthermore, scholarly investigations have demonstrated the importance of proactive decision-making support, prompt reminders, and customised incentives as a means of reducing procrastination tendencies and creating an environment conducive to the integration of fintech chatbots within the financial services industry (Azimi et al., 2020; Malodia et al., 2022).

H_6: Procrastination is positively associated with the non-adoption intention of the fintech chatbot.

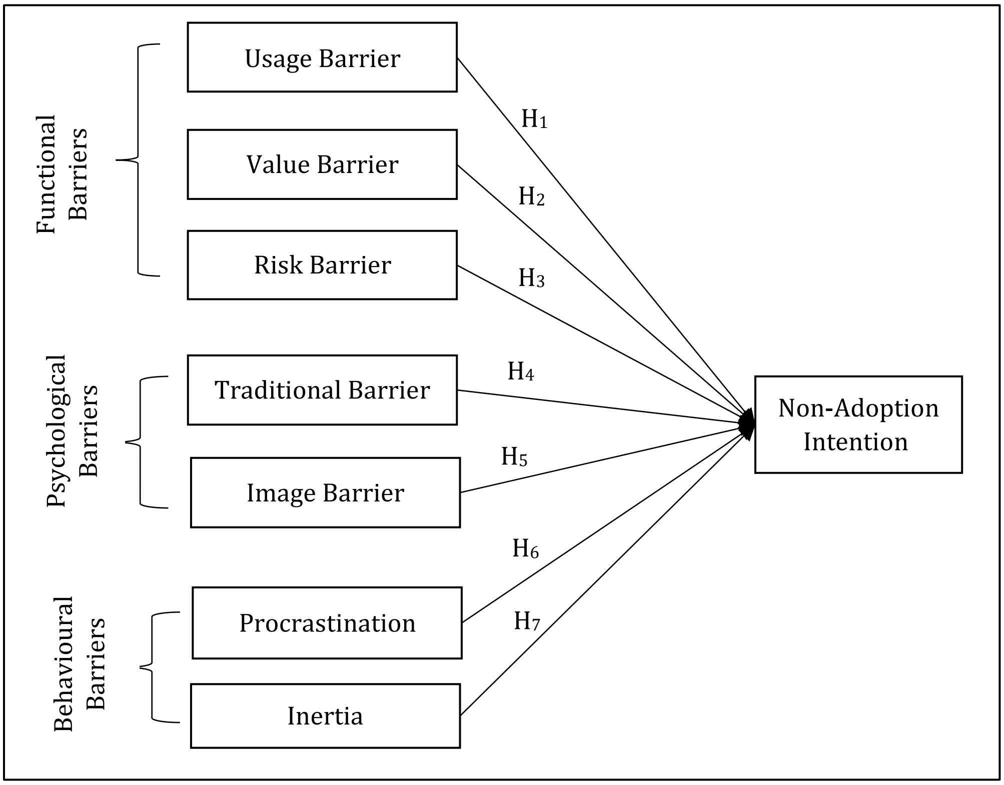
Inertia

Inertia refers to the tendency of consumers to persist in certain practices regardless of the presence of better alternatives (Malodia et al., 2022). Fintech chatbot adoption may be positively influenced by consumer inertia, which refers to the tendency of consumers to adhere to established practices despite the availability of alternatives. Users who display inertia in their task interactions are likely to express reluctance or resistance to adopting these innovative solutions due to their preference for traditional methods over the integration of new technology (Kim & Park, 2023). Researchers have found that user inertia plays a significant role in the adoption of new technologies, as well as the persistent influence of established practices on users' willingness to explore new approaches (Dwivedi et al., 2023). Moreover, scholarly investigations have indicated that tailored interventions, user-centric training, and strategic change management support are essential for addressing users' inertia and fostering a climate conducive to seamless integration of fintech chatbots into the financial services sector (Huang & Lee, 2022). Against this backdrop, the following hypothesis is formulated:

H_7: User inertia is positively associated with the non-adoption intention of the fintech chatbot.

The conceptual model of the current study is depicted in Figure 1.

Figure 1: Conceptual Model



Research Methods

Using a quantitative approach, this study examines the factors that influence user resistance to the adoption of fintech chatbots within the financial services industry. In this study, a cross-sectional design is employed to capture a snapshot of individual users' perceptions and attitudes toward chatbot technology at a specific point in time, which will provide valuable insight into the predominant barriers and behavioural tendencies influencing non-adoption intentions.

Survey Instrument

The survey instrument was structured into two sections, namely Part A and Part B. Part A primarily focused on gathering demographic information from the respondents. Part B encompassed the key items utilised to gauge the constructs outlined within the proposed research model. To ensure content validity, the measurement items for all eight constructs were adapted from prior research studies. A five-point Likert scale was employed to assess each item, with a scale ranging from 1, indicating "strongly disagree," to 5, denoting "strongly agree". Subsequently, a pilot test was conducted on the questionnaire, involving 26 participants, to assess the pertinence of the questions and their strategic placement within the survey. This process aimed to refine the questionnaire, ensuring its effectiveness in eliciting the necessary insights for the study.

The development of the survey instrument relied on the integration of established measurement items from previous research, which were subsequently contextualised to suit the present study's focus (see Appendix 1). Specifically, the measurement of the usage barrier (UB), value barrier (VB), and risk barrier (RB) drew from four items previously utilised by Laukkanen (2016). The four items to measure the tradition barrier (TB) and image barrier (IB) were adapted from Kaur et al. (2020). To evaluate the dimension of procrastination (PR), four items were adopted from the research conducted by Malodia et al. (2022). The construct of inertia (IN) was measured using four items adapted from the study by Wang et al. (2020). Finally, the dependent variable, non-adoption intention (NAI), was captured using three items adapted from the framework established by Behera et al. (2022). By leveraging these existing items, the survey instrument ensured the alignment of key constructs with established theoretical foundations while remaining relevant to the specific context of the study.

Sample and Data Collection

Since the study is focused on consumers' point of view, the respondent for the study is chosen from end users of fintech services in India, consisting of individual users using fintech payment applications and personal financial management applications. In line with the pragmatic nature of the study and the constraints of time and resources, a convenience sampling technique was employed to recruit participants. A Google Form was created and shared on online social media platforms including Facebook, WhatsApp and Telegram. It helped ensure a diverse and representative sample reflective of the broader fintech user population for this study. The minimum sample size for the study was determined using GPower software, considering an effect size of 0.15, a power level of 0.95, and a maximum allowed error of 0.05 (Campanelli et al., 2018). The calculations indicated a minimum sample size of 153. Additionally, for conducting Structural Equation Modelling (SEM) analysis, a sample size exceeding 200 is recommended (Kline, 2011). At the culmination of the survey, data were successfully collected from 294 fintech users, surpassing the required minimum sample size for the current study. After removing the incomplete responses, we got 286 usable responses to proceed with the analysis. Detailed information on the demographic characteristics of the sample is shown in Table 1.

Table 1: Sample Characteristics

Characteristics		**Frequency**	**%**
Gender	Male	149	52
	Female	137	48
	Total	286	100
Age	18-25	35	12
	26-35	244	85
	Above 35	7	3
	Total	286	100
Education	Higher Secondary	15	5
	Graduation	109	38
	PG and above	162	57
	Total	286	100
Fintech App Usage Frequency	Rarely	31	11
	Sometimes	74	26
	Always	94	32
	Often	87	31
	Total	286	100

Data Analysis and Results

This study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to comprehensively analyse the collected data and assess the proposed hypotheses. Recognised for its robustness in handling complex models and small sample sizes, PLS-SEM enabled the examination of the intricate relationships between the identified variables, providing a comprehensive understanding of the interplay between the variables.

Common Method Bias

In line with best practices for ensuring the validity and reliability of the study's findings, Harman's single-factor test was conducted to assess the potential presence of common method bias (CMB) within the collected data. The results of the analysis indicated that no single factor accounted for the variance of more than 37.28%, suggesting the absence of substantial common method bias that could unduly influence the study's outcomes. Additionally, a full collinearity test was also conducted by investigating the variance inflation factor (VIF). The VIF value ranged from 1.206 to 2.057, which is considerably lower than the threshold value of 3.3 (Kock, 2015). Consequently, CMB was not identified as a problem in this study.

Assessment of Measurement Model

The validation of the measurement model encompassed examinations of reliability, convergent validity, and discriminant validity. Construct reliability was evaluated through composite reliability and Cronbach's alpha, both recommended to exceed 0.7 for robust construct reliability (Henseler et al., 2009). In this study, composite reliability values ranged from 0.833 to 0.902, while Cronbach's alpha values ranged between 0.738 and 0.857, affirming the reliability of the measurement model (refer to Table 3). Convergent validity was ascertained using Average Variance Extraction (AVE) values for each construct, all surpassing the 0.5 threshold (ranging from 0.556 to 0.697), underscoring the measurement model's convergent validity (Hair et al., 2022). Additionally, the factor loading values for each construct exceeded the 0.6 threshold (Fornell & Larcker, 1981), further supporting the model's reliability and validity (Table 2).

Discriminant validity was assessed using the Fornell-Larcker criterion. As per this criterion, the square root of the AVE of each construct should exceed its correlation with all other constructs, as suggested by Fornell and Larcker (1981). The results of the analysis revealed that the square root of the AVE for each construct surpassed its correlation with other constructs, confirming the presence of discriminant validity (Table 3).

Table 2: Reliability and Convergent Validity

Constructs	Items	Loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Image Barrier (IB)	IB1	0.823	0.787	0.797	0.862	0.609
	IB2	0.743				
	IB3	0.782				
	IB4	0.771				
Inertia (IN)	IN1	0.845	0.855	0.857	0.902	0.697
	IN2	0.828				
	IN3	0.840				
	IN4	0.825				
Procrastination (PR)	PRC1	0.695	0.732	0.738	0.833	0.556
	PRC2	0.817				
	PRC3	0.775				
	PRC4	0.688				
Risk Barrier (RB)	RB1	0.711	0.792	0.797	0.866	0.618
	RB2	0.780				
	RB3	0.793				
	RB4	0.854				
Traditional Barrier (TB)	TB1	0.777	0.783	0.807	0.854	0.593
	TB2	0.762				
	TB3	0.789				
	TB4	0.752				
Usage Barrier (UB)	UB1	0.837	0.818	0.842	0.879	0.646
	UB2	0.863				
	UB3	0.800				
	UB4	0.706				
Value Barrier (VB)	VB1	0.821	0.804	0.818	0.872	0.630
	VB2	0.694				
	VB3	0.812				
	VB4	0.840				
Non-Adoption Intention (NAI)	NAI1	0.810	0.737	0.742	0.850	0.655
	NAI2	0.836				
	NAI3	0.781				

Table 3: Discriminant Validity

	IB	IN	NAI	PR	RB	TB	UB	VB
IB	**0.780**							
IN	0.757	**0.835**						
NAI	0.645	0.707	**0.809**					
PR	0.598	0.700	0.686	**0.746**				
RB	0.645	0.731	0.709	0.679	**0.786**			
TB	0.578	0.619	0.664	0.590	0.638	**0.770**		
UB	0.566	0.575	0.613	0.532	0.591	0.488	**0.804**	
VB	0.619	0.665	0.680	0.636	0.698	0.527	0.586	**0.794**

Note: The diagonal values in bold indicate the square root of AVE.

Assessment of Structural Model

Following the validation of the measurement model, the structural model was evaluated. This examination involved the comprehensive evaluation of R^2, Q^2, path coefficients, and *t*-values to thoroughly assess the structural relationships within the model. According to the R^2 values, the proposed model explains 67.5% of the variance in fintech chatbot non-adoption intention, demonstrating a high explanatory power. Further, the predictive accuracy of the model was assessed using the Q^2 blindfolding procedure, as outlined by Hair et al. (2019). A Q^2 value greater than zero is typically indicative of strong predictive accuracy for an endogenous construct. The calculated Q^2 value for NAI was 0.650, with all its indicators demonstrating Q^2 predict values above 0, as presented in Table 4. Moreover, the comparison between the prediction errors (RMSE) of each item within the key target construct (NAI) in the PLS-SEM model and its corresponding linear model (LM) revealed that all three NAI indicators exhibited lower RMSE values compared to the LM benchmark, highlighting the high predictive power of the model (Hair et al., 2019).

The path analysis confirmed most of the hypotheses, except for H_5. Table 5 highlights the significant findings, indicating that the usage barrier (β = 0.138, p < 0.01) exhibited a positive relationship with non-adoption intentions of fintech chatbots. Similarly, the value barrier displayed a positive influence on non-adoption intention (β = 0.170, p < 0.05). Additionally, the study established a positive association between the risk barrier and non-adoption intention (β = 0.128, p < 0.1). The analysis also revealed the significant impact of the traditional barrier on fintech chatbot non-adoption intention ($\beta = 0.167$, $p < 0.01$). Moreover, the study emphasised that procrastination significantly affected non-adoption intention ($\beta = 0.167$, $p < 0.05$). Furthermore, the results underscored the statistically significant effect of user inertia on non-adoption intention ($\beta = 0.126$, $p < 0.1$). However, the data did not support the significance of the association between the image barrier and non-adoption intention, indicating that H_5 was not supported ($\beta = 0.060$, $p = 0.314$).

Table 4: Predictive Validity

Target Construct/ Indicators	Q^2 Predict	RMSE (PLS-SEM)	RMSE (LM)
NAI1	0.433	0.567	0.617
NAI2	0.488	0.522	0.547
NAI3	0.342	0.615	0.661
NAI	0.650		

Table 5: Results of PLS-SEM Analysis

	Path	β	Standard deviation (STDEV)	*t* statistics (|O/STDEV|)	*p*	Decision
H_1	UB → NAI	0.138***	0.047	2.944	0.003	Supported
H_2	VB → NAI	0.170**	0.066	2.592	0.010	Supported
H_3	RB → NAI	0.128*	0.076	1.683	0.092	Supported
H_4	TB → NAI	0.214***	0.051	4.166	0.000	Supported
H_5	IB → NAI	0.060^{ns}	0.060	1.007	0.314	Not Supported
H_6	PR → NAI	0.167**	0.066	2.514	0.012	Supported
H_7	IN → NAI	0.126*	0.068	1.851	0.064	Supported

Note: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; ns: nonsignificant

Discussion

The present study provides valuable insights into the relationship between various barriers and user resistance to adopting fintech chatbots. In our study, we observed that the impact of innovation resistance barriers on fintech chatbot non-adoption is not uniform. The nuanced effects on non-adoption intention vary based on the specific nature of the resistance barrier. Our findings reveal a distinct pattern, with certain barriers exerting more pronounced effects.

Within the dimension of functional barriers, aligning with extant studies (Talwar et al., 2021; Laukkanen, 2016), we found that usage barriers (H_1) play a pivotal role in influencing fintech chatbot non-adoption. Users who encounter difficulty in integrating chatbots into their existing routines and workflows are more likely to refrain from adopting them. Consequently, perceptions of difficulty in understanding and implementing innovation, closely related to complexity, contribute significantly to non-adoption (Alshallaqi et al., 2022; Azimi et al., 2020). In line with prior studies (Ghosh, 2022; Kaur et al., 2020), supporting the H_2, the value barrier significantly contributes to the non-adoption of fintech chatbots. These results suggest that non-adoption increases when users perceive fintech chatbots as incapable of delivering superior functionalities compared to traditional options. Communication of chatbots' unique benefits becomes crucial to overcoming value barriers. Further, consistent with extant studies (Prakash & Das, 2022; Talwar et al., 2021), our analysis reveals that risk barriers significantly contribute to the non-adoption intention of fintech chatbots backing H_3. Users express concerns about these innovations' potential physical, economic, functional, and social risks. This perception of risk needs to be addressed and alleviated by transparent communication and robust security measures (Ghosh, 2022).

Out of the psychological barriers, the traditional barrier has a distinct impact on non-adoption, while the image barrier does not. Supporting the prior literature (Ray et al., 2020; Laukkanen, 2016) and H_4, traditional barriers demonstrated significant impacts on non-adoption. The effect sizes associated with traditional barriers were notably larger than the other barriers (β= 0.214). This indicates that the psychological relationship between users and fintech chatbots, encompassing factors like established beliefs and stereotypes, holds more weight in shaping non-adoption intentions. Similar to the hospitality industry study by Lee and Kim (2022), we also observe the same resistance to fintech chatbots when alternative services challenge established norms. These psychological challenges arise when users cannot reconcile the benefits of human interactions with those offered by fintech chatbots. It was surprising to find that contradictory to existing studies (Behera et al., 2022; Laukkanen, 2016), the image barrier has no impact on users' non-adoption intentions, indicating that usnegative perceptions of credibility and reliability about chatbot technology are unlikely to be a significant contributor to their non-adoption intentions. However, the insignificant relationship between the image barrier and resistance to technology adoption is supported by earlier research too (Kaur et al., 2020). The difference in association between these two psychological barriers with resistance is probably due to their nature. The image barrier captures resistance due to negative associations with innovation, while traditional barriers involve challenges in changing existing routines.

Transitioning to behavioural barriers, user inertia and procrastination are confirmed as significant contributors to non-adoption, supporting H_6 and H_7. Drawing from Kim and Park (2023) and Dwivedi et al. (2023), our study explored the impact of user inertia on fintech chatbot adoption. Results indicate a significant positive association between user inertia and non-adoption intention, suggesting that users' predisposition to maintain the status quo hinders their willingness to embrace innovative fintech solutions. Consistent with the literature (Malodia et al., 2022; Andersson, 2016), our study integrates procrastination as a behavioural dimension affecting fintech chatbot adoption. Results show a significant positive relationship between procrastination and non-adoption intention, emphasising the tendency of users to delay decisions related to fintech chatbot adoption.

Theoretical Implications

This research enriches the landscape of fintech adoption theories by extending the IRT. Firstly, it provided a robust research framework to understand the barriers affecting fintech chatbot non-adoption with high explanatory power (R^2=67.5). Secondly, the integration of procrastination and inertia into the IRT framework signifies a noteworthy theoretical advancement. While previous research has primarily explored how functional and psychological barriers influence innovation resistance, the introduction of procrastination and inertia provides a deeper understanding of the behavioural complexities users face in adopting fintech chatbots. This extension contributes to the theoretical foundation of fintech adoption by acknowledging that users' reluctance is not solely driven by rational concerns but also by inherent behavioural tendencies. Thus, the study offers a more comprehensive lens through which to view non-adoption decisions. Thereby, it not only enhances our understanding of user resistance but also provides a more holistic foundation for future studies in the ever-evolving fintech landscape.

Practical Implications

From a practical standpoint, the findings offer actionable insights for fintech developers, financial institutions, and policymakers. By identifying the distinct effects of different barriers, it is possible to design targeted interventions to address specific issues (Malodia et al., 2022). To alleviate barriers to usage and value, developers can improve the user interface and communication (Khanra et al., 2021).

Emphasising transparent communication and robust security measures can help mitigate risk perceptions (Kwangsawad & Jattamart, 2022). Policymakers and financial institutions need to recognise the significance of psychological factors, especially traditional barriers, and tailor awareness campaigns and educational initiatives accordingly (Behera et al., 2022; Cham et al., 2021).

Additionally, the impact of user inertia and procrastination suggests the importance of user-centric design and targeted strategies to encourage behavioural shifts (Malodia et al., 2022). Overall, these practical implications aim to guide stakeholders in developing more user-friendly and culturally sensitive fintech chatbot solutions.

Limitations and Future Research

Despite the valuable insights gained from this study, several limitations should be acknowledged, offering avenues for future research. Firstly, the research is context-specific to fintech chatbot adoption in the financial services sector. Therefore, the findings are not generalisable to other industries or types of fintech innovations. Future research could explore the nuances of user resistance in various fintech domains to establish broader patterns.

Secondly, the study primarily relies on self-reported data, which may be subject to response bias and social desirability effects. Employing diverse research methods, such as observational studies or qualitative interviews, could provide a more comprehensive understanding of user behaviour and attitudes. Another limitation involves the cross-sectional nature of the data, capturing a snapshot of user perceptions at a specific point in time. Longitudinal studies could offer insights into the dynamic nature of fintech adoption, tracking changes in user attitudes over an extended period.

Furthermore, the study focuses on a set of specific barriers, and while these are identified as significant, there may be other unexplored factors influencing fintech chatbot adoption. Future research could delve into additional dimensions of user resistance or consider cultural variations in adoption patterns. Future research could also extend the investigation into the role of user education and awareness programmes in mitigating resistance to fintech chatbot adoption. Exploring interventions that address specific barriers and assessing their effectiveness would contribute to practical implications for stakeholders in the fintech industry.

Conclusion

Utilising an extended IRT approach augmented with user inertia and procrastination, this study provided a comprehensive understanding of the factors influencing user resistance to adopting fintech chatbots within the financial services industry. It is evident from the findings that a variety of barriers, such as usage, value, risk, traditional, user inertia, and procrastination, play a significant role in determining the non-adoption intentions of users. However, the image barrier did not emerge as a significant influencing factor. In the evolving landscape of fintech chatbots, these results highlight the multifaceted nature of user resistance and the interaction between psychological, functional, and behavioural barriers.

Declaration of Conflicting Interests

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

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Appendix 1: Construct Measurement and Sources

Construct	Items	Source
Usage Barrier (UB)	UB1: It would probably not be easy to use the chatbot for financial services. UB2: It would probably not be fast to use the chatbot when I use fintech services. UB3: It would probably be confusing to use the chatbot for financial services. UB4: It would probably not be convenient to use the chatbot for financial services	Laukkanen (2016)
Value Barrier (VB)	VB1: There is no advantage to using fintech chatbot for financial services. VB2: A fintech chatbot would probably not satisfactorily deal with my problems when I using fintech services. VB3: The fintech chatbot do not provide quality service. VB4: It would probably not be easy to use the fintech chatbot.	Laukkanen (2016)
Risk Barrier (RB)	RB1: There is a privacy concern while using fintech chatbot service. RB2: I feel that the fintech chatbot service is not secure and reliable. RB3: The risk of unauthorised access to my financial accounts is higher when using fintech chatbots for financial services. RB4: I am concerned about the reliability and accuracy of the information provided by fintech chatbots for financial services.	Laukkanen (2016)
Traditional Barrier (TB)	TB1: Communication with human staff for financial services is a pleasant experience. TB2: The Chatbot's services would probably not be as satisfactory as the service I have experienced so far. TB3: The chatbot's services would probably be less trustworthy than the service I have experienced so far TB4: Traditional methods are more familiar and comfortable for financial services compared to chatbots.	Kaur et al. (2020)

Construct	Items	Source
Image Barrier (IB)	IB1: I have a very negative image of the fintech chatbot. IB2: A fintech chatbot would probably often be too complicated to be useful. IB3: I have an image that a fintech chatbot's services are difficult to use. IB4: In my opinion, new technology is often too complicated to be useful.	Kaur et al. (2020)
Procrastination (PR)	PR1: I take a lot of time on trivial matters before deciding on new technology such as fintech chatbot. PR2: Even after I have made a decision to adopt new technology such as fintech chatbot, I delay acting upon it. PR3: When I have to make a decision to use new technology such as fintech chatbot, I wait a long time before starting to think about it. PR4: I put off making decisions related to adopting new technology such as fintech chatbot.	Malodia et al. (2022)
Inertia (IN)	IN1: I generally consider the change as a negative thing. IN2: I would rather do the same old things than try new ones IN3: In my opinion, the existing customer service system available were satisfactory so far. IN4: In general, I resist to change.	Wang et al. (2020)
Non-Adoption Intention (NAI)	NAI1: I do not have the intention to use fintech chatbot in the future. NAI2: I would not recommend others to use fintech chatbot. NAI3: I will not use fintech chatbot in the future	Behera et al. (2022).