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Consumer resistance to AI chatbots: barriers and impacts on negative word-of-mouth

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Abstract

Purpose – This study aims to investigate the effects of functional and psychological barriers on consumer resistance to adopting AI-powered conversational agents (AICAs) in financial services and their implications for negative word-of-mouth (NWOM).

Design/methodology/approach – This study used an online survey to collect data from a sample of 294 AICA users. This study uses partial least squares structural equation modeling to evaluate the study's hypotheses.

Findings – The findings of this study reveal that usage, risk and tradition barriers significantly influence consumer resistance, in contrast to value and image barriers. Furthermore, consumer resistance significantly influences NWOM. Additionally, resistance fully mediates the relationships between usage and risk barriers, and NWOM partially mediates the relationship between tradition barriers and NWOM.

Originality/value – This study extends the Innovation Resistance Theory into the domain of AICA adoption, exploring the nuanced effects of IRT barriers on consumer resistance and NWOM. This study highlights the mediating role of consumer resistance in the relationship between barriers and NWOM, providing actionable insights for service providers and advancing technology adoption and resistance research.

Keywords AI-powered conversational agents, Chatbot, Consumer resistance, Negative word-of-mouth, Financial services, Innovation resistance theory

Paper type Research paper

Resistencia del consumidor a los chatbots con IA: Barreras e impactos en el boca a boca negativo

Resumen

Objetivo – Este estudio tiene como objetivo investigar los efectos de las barreras funcionales y psicológicas sobre la resistencia del consumidor a adoptar agentes conversacionales impulsados por IA (AICA) en servicios financieros, y sus implicaciones para el boca a boca negativo (NWOM).

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Data accessibility: The data sets supporting this study's findings are available upon reasonable request from the corresponding author.

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Diseño/metodología/enfoque/metodología/enfoque – El estudio utilizó una encuesta en línea para recopilar datos de una muestra de 294 usuarios de AICA. Se empleó el modelado de ecuaciones estructurales mediante mínimos cuadrados parciales (PLS-SEM) para evaluar las hipótesis del estudio.

Resultados – Los resultados revelan que las barreras de uso, riesgo y tradición influyen significativamente en la resistencia del consumidor, a diferencia de las barreras de valor e imagen. Además, la resistencia del consumidor influye significativamente en el NWOM. Asimismo, la resistencia media completamente las relaciones entre las barreras de uso y riesgo y el NWOM, y media parcialmente la relación entre las barreras de tradición y el NWOM.

Originalidad/valor/valor – Este estudio amplía la Teoría de Resistencia a la Innovación (IRT) al ámbito de la adopción de AICA, explorando los efectos diferenciados de las barreras de la IRT sobre la resistencia del consumidor y el NWOM. Destaca el papel mediador de la resistencia del consumidor en la relación entre las barreras y el NWOM, aportando información práctica para los proveedores de servicios y avanzando en la investigación sobre adopción y resistencia tecnológica.

Palabras clave Agentes conversacionales con IA, Chatbot, Resistencia del consumidor, Boca a boca negativo, Servicios financieros, Teoría de resistencia a la innovación
Tipo de artículo Trabajo de investigación

消费者对人工智能聊天机器人的抗拒：障碍及其对负面口碑的影响

摘要

研究目的 – 本研究旨在探讨功能性与心理性障碍对消费者在金融服务场景中采纳人工智能聊天代理（AICA）时抗拒行为的影响, 并进一步分析消费者抗拒对负面口碑（NWOM）传播的作用机制。

研究方法 – 本研究通过在线问卷调查, 收集了294名实际使用过AICA的消费者样本数据, 采用偏最小二乘结构方程建模（PLS-SEM）方法对提出的研究模型与假设进行了实证检验。

研究结果 – 研究结果表明, 使用障碍、风险障碍与传统障碍对消费者抗拒行为具有显著正向影响, 而价值障碍与形象障碍的影响并不显著。此外， 消费者抗拒行为对负面口碑传播具有显著促进作用。进一步分析显示, 抗拒行为在使用障碍和风险障碍影响负面口碑的路径中起完全中介作用，在传统障碍影响负面口碑的路径中则发挥部分中介作用。

原创性/价值 – 本研究将创新抗拒理论（IRT）应用于人工智能聊天代理（AICA）采纳领域, 系统揭示了不同类型障碍对消费者抗拒及负面口碑传播的差异化影响机制。通过强调抗拒行为在障碍与负面口碑关系中的中介作用，丰富了技术采纳与抗拒领域的理论体系，同时为金融服务领域的人工智能应用推广提供了实践启示。

关键词 人工智能聊天代理, 聊天机器人, 消费者抗拒, 负面口碑, 金融服务, 创新抗拒理论
文章类型 研究型论文

Introduction

AI-powered conversational agents (AICAs) or chatbots are AI-based interfaces that imitate human communication through written or oral means using natural language processing and machine learning (Hentzen *et al.*, 2022; Jan *et al.*, 2023; Yang *et al.*, 2023). The projected growth of the chatbot in the global Banking, Financial Services and Insurance sector, expected to increase from US$586m in 2019 to US$6.83bn by 2023 (Vailshery, 2022). However, 54% of consumers avoid chatbots for sensitive financial matters (McNamee, 2022), highlighting the importance of understanding the factors driving resistance to AICAs.

The extant literature focuses on chatbot adoption in financial services, neglecting resistance, especially in emerging markets such as Egypt (Chaouali *et al.*, 2024; Jisham *et al.*, 2024). On the other hand, findings from developed contexts often fail to account for the cultural and infrastructural complexities of developing markets, where consumer resistance is influenced by fragile banking systems, concerns over e-banking quality and fear of electronic fraud (Elsotouhy *et al.*, 2023). This study addresses this gap by examining consumer resistance in this context.

In Egypt, financial service usage is growing, with internet penetration reaching 72.2% (Go-Globe, 2024), and financial service accounts increasing by 181% between 2016 and 2024 (CBE, 2024). However, cultural and psychological barriers shape consumer resistance, causing a decrease in the adoption rate of financial technologies such as mobile payments, mobile banking and e-wallets (Bakr *et al.*, 2023; El Din *et al.*, 2023). Despite increasing financial inclusion, there is a limited understanding of consumer resistance to AICA in the Egyptian context (El Din *et al.*, 2023; El-Shihy *et al.*, 2024), highlighting a critical gap.

This study adopts Innovation Resistance Theory (IRT) (Ram and Sheth, 1989) to explore consumer resistance to AICAs in financial services. In contrast to the novelty-seeking paradigm (e.g. UTAUT and TAM) that focuses on adoption drivers, IRT focuses on functional and psychological barriers, such as perceived risks, complexity and traditional preferences (Jan *et al.*, 2023; Yang *et al.*, 2023). This framework is particularly relevant for Egypt's banking sector, where cultural, infrastructural and psychological factors significantly influence resistance to digital transformation (Elsotouhy *et al.*, 2023).

However, despite the advantages of IRT, previous studies have revealed inconsistencies in understanding the barriers that shape consumer innovation resistance (CIR) (Table 1). Such contradictions highlight the need for further exploration of the specific barriers that influence the resistance to AICAs. This leads to the first research question:

RQ1. What functional and psychological barriers are significant for consumers' resistance to chatbots?

Additionally, previous studies examined the impact of IRT barriers on outcomes such as intention to use (Migliore *et al.*, 2022), actual usage (Sivathanu, 2019), non-adoption intention (Behera *et al.*, 2023), hedonist, social and actualized innovativeness (Chu, 2023). However, limited attention has been paid to negative word-of-mouth (NWOM) (Jana, 2022), which is a critical consequence of resistance (Hentzen *et al.*, 2022; Huang *et al.*, 2021). Previous studies on financial service chatbots indicate that individuals who resist chatbots tend to disseminate unfavorable details regarding this innovation (Jana, 2022), which can

Table 1. A synthesis of prior research reveals inconclusive findings regarding innovation barriers

Study	Context	UB	VB	RB	TB	IB
Baklouti and Boukamcha (2024)	Internet banking	NS	NS	S	S	S
Bhatnagr *et al.* (2024)	Neo-banking	S	S	S	S	NS
Jisham *et al.* (2024)	Fintech	S	S	S	S	NS
Chang and Hsiao (2024)	Customer service chatbot	NS	S	S	NS	NS
Behera *et al.* (2023)	Mobile payments	S	S	S	S	S
Chu (2023)	Driver assistance systems	S	S	S	NS	S
Jana (2022)	Digital payment systems	S	NS	S	NS	S
Khanra *et al.* (2021)	Mobile payments	S	NS	NS	NS	S
Cheng *et al.* (2018)	E-wallet	S	S	S	S	NS
Leong *et al.* (2020)	E-wallet	S	S	S	S	NS
Sivathanu (2019)	Digital payment systems	S	S	S	S	S
Mani and Chouk (2018)	Internet of Things	S	NS	S	S	S
Chen (2018)	Hydrogen-electric motorcycles	S	N	S	S	NS

Note(s): S = significant positive effect, NS = non-significant effect, N = negative association, UB = Usage barriers, VB = Value barriers, RB = Risk barriers, TB = Tradition barriers and IB = Image barriers discourage adoption and increase resistance (Mani and Chouk, 2018). This is particularly relevant in Egypt, where trust and human interaction are pivotal (Elsotouhy *et al.*, 2023; Esawe, 2022). This prompts the following question:

RQ2. How does consumer resistance to chatbots influence negative word-of-mouth?

Previous studies on IRT barriers' influence on recommendation behavior have inconclusive results (Kaur *et al.*, 2020, 2021; Talwar *et al.*, 2021), indicating an overlooked mediating mechanism (Jana, 2022). NWOM significantly impacts businesses because responses to both functional and psychological barriers can lead to consumer resistance (Chu, 2023; Leong *et al.*, 2021), negative emotions (Chang and Hsiao, 2024) and the propagation of NWOM (Talwar *et al.*, 2021), affecting profitability and customer engagement. This leads to the third research question:

RQ3. How does consumer resistance to chatbots mediate the relationship between Innovation Resistance Theory barriers and negative word-of-mouth?

Guided by prior research, the first objective of this study is to investigate the impact of functional and psychological barriers on consumer resistance to AICA adoption. Second, it identifies the impact of CIR on NWOM. Finally, it examines the mediating role of CIR in the relationship between these barriers and NWOM.

This research has both theoretical and practical contributions, as it adds to the existing scant knowledge regarding chatbots in financial services by identifying the impact of usage, risk, tradition, value and image barriers (IBs) on CIR; extending the theoretical understanding of CIR and NWOM in the context of financial services; exploring the mediating effects of CIR on the relationship between functional and psychological barriers and NWOM; and providing actionable insights for financial service providers to address consumer resistance and provide guidance on integrating chatbot tools into customer support.

Theoretical literature

Literature review

Artificial intelligence in customer-facing financial services. AI systems have become game changers in financial services, offering opportunities, such as reducing costs, enhancing customer experience, providing better services and increasing efficiency (Akyüz and Mavnacıoğlu, 2023). Chatbots are widely adopted across sectors including banking (Abdel Wahab, 2023) and insurance (Dekkal *et al.*, 2023; Patil *et al.*, 2024). Banks use chatbots to offer immediate customer services or redirect customer inquiries to appropriate service employees, thus enhancing the customer experience (CFPB, 2023). However, the implementation of chatbots remains challenging. For instance, although anthropomorphic chatbots may build psychological attachments, they can also raise privacy concerns, discomfort and perceived intrusiveness in critical financial decisions (El Din *et al.*, 2023; Patil *et al.*, 2024; Zhu, 2023).

Customers often experience frustration from automated systems that hinder communication with employees or respond inappropriately to user requests because of their limited conversational capabilities (CFPB, 2023). These limitations create a discrepancy between user expectations and service performance (Yang *et al.*, 2023). Such issues contribute to unfavorable customer behaviors, including resistance, which negatively affects service providers and customers (Akyüz and Mavnacıoğlu, 2023).

Existing literature explores the technical aspects and characteristics of chatbots, such as their interface design, interaction capabilities and AI-based natural language processing (Mariani *et al.*, 2023). Additionally, studies have examined user experiences and preferences, including perceptions of human likeness, trust in chatbots (El Din *et al.*, 2023; Patil *et al.*, 2024; Zhu, 2023) and chatbot visual and conversational design (Li *et al.*, 2021). However, few studies have addressed the barriers that contribute to consumer resistance (Jisham *et al.*, 2024). Understanding resistance and its impact on financial services is crucial to bridging these gaps and mitigating consumer resistance (Dekkal *et al.*, 2023).

Innovation resistance theory. The IRT explores consumer resistance as a distinct behavior, not merely as an antithesis of acceptance (Esawe *et al.*, 2023; Santos and Ponchio, 2021). Ram and Sheth (1989, p.6) defined innovation resistance (IR) as “the resistance offered by consumers to an innovation, either because it poses potential changes from a satisfactory status quo or because it conflicts with their belief structure.” Propagation mechanisms (situation) and perception of innovation or consumer characteristics are significant factors that can lead to two distinct types of innovation resistance: passive and active (Heidenreich and Handrich, 2015; Ram and Sheth, 1989).

In passive resistance, individuals are satisfied with the status quo and unconsciously inclined to reject any change imposed by an innovation that may contradict their prior views or existing state, even before evaluating the innovation (Heidenreich and Handrich, 2015; Heidenreich and Kraemer, 2015; Heidenreich and Spieth, 2013; Laukkanen, 2016). This rejection is related to psychological barriers such as image and tradition (Esawe *et al.*, 2023; Ram and Sheth, 1989). On the other hand, active innovation resistance is a deliberate form of resistance formed after a careful evaluation of innovation attributes in relation to consumer expectations (Esawe *et al.*, 2023; Santos and Ponchio, 2021). It is driven by functional barriers, such as risks, use and costs, when individuals face potential conflicts between certain attributes and expectations (Ram and Sheth, 1989; Talke and Heidenreich, 2014).

Previous studies have applied IRT to various innovations including sustainable innovation (Esawe *et al.*, 2023) and driver assistance systems (Chu, 2023). Some scholars have used IRT exclusively (Talwar *et al.*, 2020), while others have supplemented IRT with relevant theories, such as the UTAUT2 model (Migliore *et al.*, 2022) and social support theory (Khaw *et al.*, 2022). Consumer intention and behavior toward innovation can be understood through two lenses: the adoption lens and the resistance lens. The adoption lens (e.g. UTAUT and TAM) examines adoption facilitators, where TAM identifies ease of use and perceived usefulness as adoption drivers (Elsotouhy *et al.*, 2023), and UTAUT considers effort expectancy, performance expectancy, social influence and facilitating conditions (Esawe, 2022). The resistance lens IRT uniquely focuses on functional and psychological barriers that increase resistance, making it highly relevant to understanding resistance to AI chatbots (Jisham *et al.*, 2024). However, studies have suggested that barriers often exhibit asymmetrical effects with incongruities in comprehensiveness and understanding that require further investigation (Leong *et al.*, 2021). Thus, IRT serves as a critical lens for examining the interplay between resistance factors and consumer behavior in contexts such as AI in customer-facing financial services.

Hypotheses development

Usage barriers and consumer innovation resistance. Usage barriers (UBs) are emerging because of compatibility and complexity issues (Leong *et al.*, 2021). The former increases when innovation contradicts consumers’ current usage experience and established routines (Ram and Sheth, 1989). The latter involves: innovation as an abstract idea (is it easy to understand?) and implementation complexity (is it easy to use?) (Laukkanen, 2016; Talwar *et al.*, 2020). Higher compatibility and complexity lead to higher resistance and rejection (Ram, 1989; Jana, 2022). In customer-facing financial services, chatbot limitations, such as repetitive loops or reliance on complex large language models, hinder meaningful conversations and complicate obtaining clear and reliable answers conversation (CFPB, 2023; Yang *et al.*, 2023). Previous studies have confirmed a positive relationship between UB and CIR (Bhatnagr *et al.*, 2024; Leong *et al.*, 2021). Thus, chatbot attributes such as compatibility and complexity remain critical factors influencing chatbot resistance (Jana, 2022; Jisham *et al.*, 2024). Based on these arguments, the following is proposed:

H1. Usage barriers positively influence consumer resistance to chatbot use.

Value barriers and consumer innovation resistance. A value barrier (VB) is perceived when innovation has extraordinarily little or no added value (price-to-performance tradeoff) compared with its substitutes (Ram and Sheth, 1989). Consumers consider the innovation they use as reference points, and if the new one lacks superior value, then they are unlikely to change their habits or routines; consequently, they will not consider switching (Laukkanen, 2016) and may even resist it (Leong *et al.*, 2021). In financial services, rigid chatbot protocols that fail to accommodate the diversity and privacy inherent in individual queries fade the perceived value (Chaouali *et al.*, 2024). In addition, chatbots provide insufficient assistance and hinder interactions with human agents, which may lead to additional costs for consumers (CFPB, 2023). Such limitations contribute to resistance, as consumers prefer the superior benefits of interacting with human agents over chatbots (Jana, 2022). Prior studies have suggested a positive correlation between VBs and CIR (Baklouti and Boukamcha, 2024; Bhatnagr *et al.*, 2024). Based on this, the following is proposed:

H2. Value barriers positively influence consumer resistance to chatbot use.

Risk barriers and consumer innovation resistance. Consumers perceive risks as uncertainties that could threaten their adoption (Esawe, 2022). Perceived risks such as privacy breaches, impersonation, phishing fraud and security vulnerabilities (Huang *et al.*, 2021; Leong *et al.*, 2021; Xie *et al.*, 2024) significantly shape and drive consumer resistance to chatbots (Chang and Hsiao, 2024). Consumers who perceive chatbots to be less secure than traditional methods prefer interpersonal interactions with human agents (Jisham *et al.*, 2024). Poorly designed chatbots or a lack of customer support can exacerbate these concerns, leading to a loss of customer trust and heightened resistance (CFPB, 2023). Additionally, fear of errors or third-party privacy violations during chatbot usage further increases apprehension (Chaouali *et al.*, 2024; Cheng *et al.*, 2018; Laukkanen, 2016; Santos and Ponchio, 2021). While some studies confirm a positive effect of risk barriers (RBs) on CIR in financial services (Behera *et al.*, 2023; Bhatnagr *et al.*, 2024; Jana, 2022), Khanra *et al.* (2021) find an insignificant effect. Therefore, the following is proposed:

H3. Risk barriers positively influence consumer resistance to chatbot use.

Tradition barriers and consumer innovation resistance. Consumers may perceive tradition barriers (TBs) when an innovation clashes with existing traditions, values, beliefs, norms and culture (Kleijnen *et al.*, 2009; Ram and Sheth, 1989). This barrier is also observed when consumers prefer traditional ways of interacting (Laukkanen, 2016). When deviating from an established routine, clients often feel frustrated because of anxiety about a perceived loss of control (Mani and Chouk, 2018), leading them to prefer familiar services, as the interactions with chatbots markedly contrast with traditional interaction methods that many customers associate with valued interpersonal engagement (Chaouali *et al.*, 2024). If interacting with a chatbot leads or forces consumers to change routines or clash with their culture, then they are likely to display increased resistance toward its adoption (Jana, 2022). Prior studies have suggested a positive correlation between traditional barriers and CIR (Baklouti and Boukamcha, 2024; Bhatnagr *et al.*, 2024). Therefore, the following is proposed:

H4. Tradition barriers positively influence consumer resistance to chatbot use.

Image barriers and consumer innovation resistance. Innovation origins, such as country of origin, product category or brand, give innovation its own identity, which can lead to a negative image associated with innovation (Laukkanen, 2016). Another reason is consumers may perceive it as difficult to use (Ram and Sheth, 1989). These barriers positively affect resistance toward digital payment systems (Sivathanu, 2019), mobile payment services (Behera *et al.*, 2023; Khanra *et al.*, 2021) and neo-banking (Bhatnagr *et al.*, 2024). In the context of chatbot, if consumers have a negative image about chatbots or believe they are difficult to use, then their resistance will be stronger (Jana, 2022). Therefore, the following is proposed:

H5. Image barriers positively influence consumer resistance to chatbot use.

Consumer innovation resistance and negative word-of-mouth. According to Kaur *et al.* (2021, p. 1747), CIR is “the behavior toward the adoption and usage of any innovation that results in maintaining the status quo and resisting any deviances from the current beliefs.” Consumers who exhibit resistance to innovations are inclined to criticize and actively oppose innovation, which hampers its success (Kleijnen *et al.*, 2009). Word-of-mouth (WOM) is a significant factor in innovation and can lead to NWOM if customers have an unpleasant experience (Kaur *et al.*, 2021). These resistance consumers can have a negative impact on not only their immediate social connections but also society (Jana, 2022). Consequently, consumers who resist chatbots actively attack and oppose them, affecting their success and influencing the adoption decisions of other consumers. According to Jana (2022), consumer resistance leads to NWOM. Therefore, the following is proposed:

H6. Consumer resistance to using chatbot positively influences negative word-of-mouth.

The mediating effect of consumer resistance. Consumer resistance toward innovation may be linked to conservative attitudes, such as a preference for cognitive closure and anti-hedonic approaches, resulting in brand loyalty, aversion to new options and preference for nostalgic products. Additionally, CIR is often driven by functional and psychological barriers (Leong *et al.*, 2021). These barriers create dissatisfaction and mistrust, leading to resistance and ultimately NWOM (Méndez-Suárez and Danvila-Del-valle, 2023). Previous studies highlight that IRT barriers can increase CIR (Behera *et al.*, 2023; Bhatnagr *et al.*, 2024; Jisham *et al.*, 2024), whereas resistant consumers may actively spread NWOM to discourage others from adopting disruptive innovations (Jana, 2022; Talwar *et al.*, 2021).

This study builds on Jana's (2022) findings on chatbots in financial services, proposing that CIR serve as an intermediate mechanism linking IRT barriers to NWOM in the chatbot context. By investigating how resistance translates barriers into adverse word-of-mouth, this study enriches IRT by exploring a nuanced behavioral dynamic. Thus, this study proposes the following hypotheses:

H7. Consumer resistance to chatbot mediates the relationship between (*H7a*) usage barrier; (*H7b*) value barrier; (*H7c*) risk barrier; (*H7d*) tradition barriers; (*H7e*) image barriers and negative word-of-mouth.

Figure 1 schematizes this study's conceptual framework.

Methods

Sampling and data collection

This study targeted users of the chatbot services offered by Egyptian banks. As there was no accessible sampling frame, we used purposive (judgment) sampling to ensure the inclusion of participants with relevant experience (Bougie and Sekaran, 2019). Participants were recruited via social media platforms such as Facebook and Twitter using a structured questionnaire hosted on Google Forms. Three postgraduate students with expertise in market research were trained by the researcher to facilitate the distribution and data collection processes. Rigorous quality controls were implemented, including single-response restrictions and a screening question to restrict access to customers who had no prior experience using financial services chatbots, maintaining the focus of the study.

The final data collection spanned six weeks between January and February 2024, yielding 312 responses. After 18 incomplete questionnaires were excluded, a final sample of 294 responses were retained for analysis. This sample size surpassed the minimum sample size of 138 estimated using G*Power v3.1 software with specific parameters (effect size = 0.15, α = 0.05, power = 0.95 and number of predictors = 5) (Erdfelder *et al.*, 2009). Male and female participants were 60.9% and 39.1%, respectively, and the average age of the respondents was 21–30 years, which is considered tech-savvy. Approximately 24.1% had used chatbots for more than two years (Table 2).

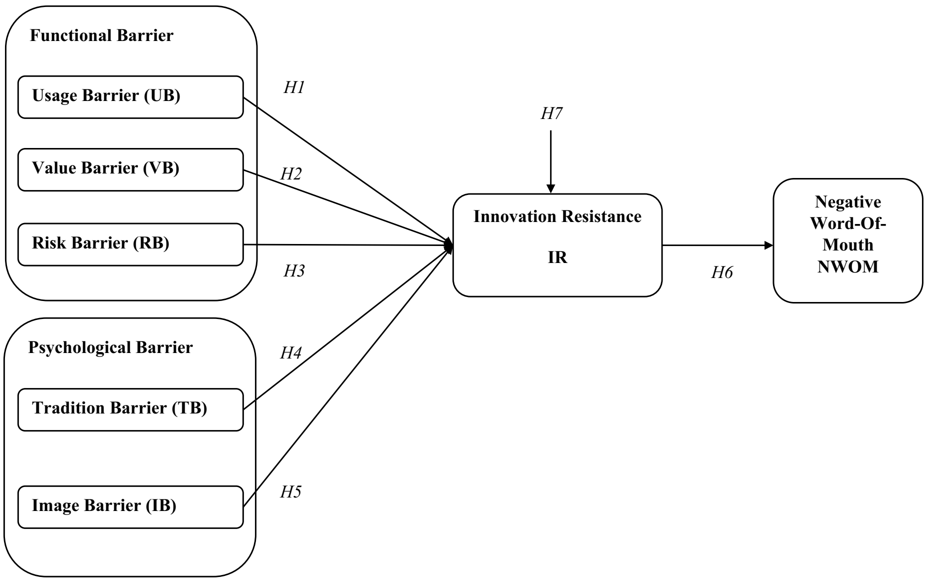

Figure 1. Conceptual framework

Table 2. Descriptive statistics of respondents

Variable	Cases (%)
Gender	
Male	179 (60.9)
Female	115 (39.1)
Age	
21–30 years	215 (73.1)
31–40 years	12 (4.1)
41–50 years	45 (15.3)
51 years or older	22 (7.5)
Length of use	
Less than six months	58 (19.7)
Six months– one year	64 (21.8)
One year – less than one and half year	54 (18.49)
one and half years- two years	47 (16.0)
More than two years	71 (24.1)

Measurement scales

We adopted multiple items to measure each latent variable from previously validated scales in the literature, resulting in 31 items (Table 3). Each item was rated on a seven-point Likert scale, ranging from “strongly disagree” to “strongly agree.” To avoid translation bias, a back-translation method was used, as all constructs were translated from English to Arabic, the primary language in Egypt (Behr, 2017). The questionnaire consisted of two parts: the participants’ personal information and questions related to the endogenous and exogenous variables used in the study.

Initially, a pre-test was conducted involving a committee of three professionals and four academic experts to improve the instrument and ensure adequate face validity. Subsequently, a pilot test was conducted with 59 chatbot service users to identify areas for improvement in the questionnaire and assess the factor loadings for all the latent constructs, which ranged from 0.706 to 0.982.

Common method bias

This study followed the recommendations of Podsakoff *et al.* (2003) to mitigate common method bias (CMB). Procedural remedies included using a concise, straightforward survey with validated scales to minimize ambiguity and redundancy, providing clear instructions, explaining objectives and assuring respondents confidentiality and anonymity. To reduce response bias, the dependent and independent variables were spatially separated. Statistically, Harman’s single-factor test confirmed factor accounted for more than 50%, with the first factor accounting for only 36.58% of the variance, thus supporting the robustness of the findings.

Data analysis

We used partial least squares structural equation modeling (PLS-SEM) and used SEMinR to evaluate the measurement model and estimate the structural model following the two-stage approach (Hair *et al.*, 2021). This study uses PLS-SEM as an alternative to covariance-based SEM because of its advantages in terms of fewer restrictive assumptions, making it widely used in experimental research (Sarstedt *et al.*, 2021). Specifically, PLS-SEM is preferred when the study’s primary objectives are confirmatory and explanatory modeling objectives (Benitez *et al.*, 2020).

Table 3. Scale refinement results

Measurement Items	Factor loadings
Usage Barrier (UB)	
Adapted from Cheng *et al.* (2018) and Santos and Ponchio (2021) *α = 0.893; CR = 0.926; AVE = 0.757*	
Using chatbot was difficult for me	0.863
Using chatbot was inconvenient for me	0.860
Chatbot often lags or works slowly	0.875
The steps to using chatbot are not clear to me	0.881
Value Barrier (VB)	
Adapted from Laukkanen (2016) and Santos and Ponchio (2021) *α = 0.826; CR = 0.885; AVE = 0.658*	
Chatbot does not offer any advantage compared with human interacting	0.822
Using chatbot does not increase my ability to control my financial matters alone	0.774
Chatbot is not a superior substitute for traditional interact	0.846
Chatbots do not save time when interacting with it	0.800
Risk Barrier (RB)	
Adapted from Cheng *et al.* (2018); Kaur *et al.* (2020) and Laukkanen (2016) *α = 0.898; CR = 0.929; AVE = 0.765*	
I fear making mistakes in the process of using chatbot	0.894
I fear entering the wrong information when using chatbot	0.868
I fear exposure of privacy to third parties when using chatbot	0.873
I am not sure that chatbot works as promised	0.862
Tradition Barrier (TB)	
Adapted from Kaur *et al.* (2020) and Laukkanen (2016) *α = 0.897; CR = 0.929; AVE = 0.765*	
I find it difficult to get some information about chatbot use	0.882
I find it difficult to get my problem resolved by chatbot	0.872
The customer service offered by chatbot is not very pleasant	0.888
Chatbot service is not good	0.855
Image Barrier (IB)	
Adapted from Laukkanen (2016) and Santos and Ponchio (2021) *α = 0.810; CR = 0.875; AVE = 0.636*	
I have only a negative feeling about chatbot	0.789
Chatbot are often too complicated to be useful	0.782
I don't like chatbots	0.822
I have an image that chatbot is difficult to use	0.797
Consumer resistance to innovation (CRI)	
Adapted from Ju and Lee (2021) and Cheng *et al.* (2018) *α = 0.899; CR = 0.929; AVE = 0.766*	
Chatbot services are not for me	0.878
I fear of wasting my time using chatbot services	0.877
I do not need chatbot services	0.887
It is unlikely that I will use chatbot services in the near future	0.860
Negative word of mouth (NWOM)	
Adapted from Jana (2022) and Talwar *et al.* (2021) *α = 0.861; CR = 0.904; AVE = 0.703*	
I spread negative comments about the chatbot service	0.868
I share negative opinions about the chatbot service	0.874
I take active part in negative discussions related to the chatbot service	0.808
I would be very likely to warn my friends not to use the chatbot service	0.801

Note(s): *α* = Cronbach's alpha, CR = composite reliability and AVE = average variance extracted

A two-stage approach was used to analyze the data in this study (Sarstedt *et al.*, 2021). The first stage involved evaluating the measurement model by examining indicators and internal consistency, as well as validity (convergent and discriminant). The second stage consisted of assessing the structural model by examining collinearity issues, the significance and relevance of the model's relationships and the model's explanatory and predictive power (Hair *et al.*, 2021).

Results

Measurement model

In the first stage, to validate the measurement model, we assessed the reliability, convergent validity and discriminant validity of the constructs (Hair *et al.*, 2021). Table 3 presents the results, which indicate that Cronbach's (α) values ranged from 0.810 to 0.899, composite reliabilities (CR) ranged from 0.875 to 0.929 (Fornell and Larcker, 1981), average variances extracted (AVE) ranged from 0.636 to 0.766 (Kwong and Wong, 2016) and standardized factor loadings ranged from 0.782 to 0.888 (Hair *et al.*, 2019). All these values exceeded the recommended thresholds, indicating sufficient reliability and convergent validity (Sarstedt *et al.*, 2021).

To analyze the discriminant validity of the latent variables, we used the Heterotrait–Monotrait ratio (HTMT) criterion (Henseler *et al.*, 2015). Table 4 presents the HTMT values, which confirm the discriminant validity as the highest HTMT value is 0.679, below the threshold value of 0.85 (Benitez *et al.*, 2020).

Structural model analysis

In the second stage, we evaluated collinearity issues to ensure the absence of high correlations among the constructs in the structural model. According to Table 4, all VIF values were ≥ 3–5, suggesting that collinearity was not a critical issue in the structural model (Hair *et al.*, 2019).

Next, we used a bootstrap routine with 10,000 iterations to evaluate the relevance and significance of the path coefficients (Hair *et al.*, 2021). Hair and Alamer (2022, p. 7) suggest that "path coefficients (β) in the structural model ranging from 0 to 0.10, 0.11–0.30, 0.30–0.50, and > 0.50 are indicative of weak, modest, moderate, and strong effect sizes." Table 5 displays the results, indicating that *H1*, *H3*, *H4* and *H6* are supported, as evidenced by the *t*-test values (*t*-values ≥ 1.96; and p < 0.001). Specifically, TB (β = 0.333, CI 95% [0.212, 0.434]; moderate effect size), UB (β = 0.249, CI 95% [0.125, 0.363]; modest effect size) and RB (β = −0.201, CI 95% [0.109, 0.292]; modest effect size) all exhibited a positive and significant influence on CIR. However, *H2* and *H5* are not supported. VB (β = 0.066, CI 95% [−0.032, 0.153]; modest effect size) and IB (β = 0.009, CI 95% [−0.080, 0.099]; weak effect size) have no significant effect on CIR. Finally, CIR (β = 0.171, CI 95% [0.050, 0.274]; moderate effect size) positively and significantly influenced NWOM.

Table 4. Discriminant validity (HTMT) and VIF

Construct	1	2	3	4	5	6	VIF
1. Usage barrier							1.859
2. Value barrier	0.631						1.624
3. Risk barrier	0.547	0.534					1.512
4. Tradition barrier	0.556	0.532	0.386				2.012
5. Image barrier	0.450	0.440	0.369	0.679			1.565
6. Consumer Innovation resistance	0.615	0.517	0.520	0.624	0.449		1.827
7. NWOM	0.526	0.511	0.438	0.548	0.512	0.537	

Table 5. Results of structural model path coefficient

H	Relationship	β	*t*-statistics	5% CI	95% CI	Decision	F2
H1	Usage barrier → CIR	0.249	3.45***	0.125	0.363	S	0.065
H2	Value barrier → CIR	0.066	1.175	−0.032	0.153	NS	0.005
H3	Risk barrier → CIR	0.201	3.613***	0.109	0.292	S	0.051
H4	Tradition barrier → CIR	0.333	4.910***	0.212	0.434	S	0.112
H5	Image barrier → CIR	0.009	0.173	−0.077	0.100	NS	0.000
H6	CIR → NWOM	0.495	0.483***	0.308	0.620	S	0.325

Note(s): UB = Usage barrier, VB = Value barrier, RB = Risk barrier, TB = Tradition barrier, IB = Image barrier, CIR = Consumer innovation resistance, D = Decision, S = Supported, NS = Not supported and H = Hypothesis, f^2 = effect size and *p*-value (* = $p < 0.05$ and *** = $p < 0.001$)

The in-sample predictive power (explanatory power) of the model was assessed using R^2 and f^2. Hair *et al.* (2021) stated that "R^2 values of 0.75, 0.50, and 0.25 can be considered substantial, moderate, and weak, respectively." The R^2 values for CIR = 0.454 can be considered moderate, whereas the R^2 value of NWOM = 0.25 is weak. It is worth noting that the addition of the mediating effect and barriers direct effects on NWOM to the model increased the R^2 value of NWOM to 0.38.

Moreover, the results in Table 5 imply that the rank order of f^2 corresponds directly to the rank order based on the path coefficients. The f^2 value of CIR → NWOM (0.325) implies that CIR has medium effect size on NWOM, whereas the f^2 values of TBs → CIR (0.112), UBs → CIR (0.065) and RBs → CIR (0.051) imply that they have small effect sizes on CIR. On the contrary, the VBs and IBs have no effect size on CIR (Hair *et al.*, 2021).

The predictive power of the model was assessed using the $PLS_{predict}$ procedure recommended by Hair *et al.* (2021), and the direct antecedents approach was adopted (Shmueli *et al.*, 2019), in which both the antecedent and the mediator would consider in the $PLS_{predict}$ as predictors of outcome constructs (Danks, 2021). Initially, the prediction error was evaluated, revealing significant skewness (Figure 2). Consequently, the mean absolute error metric is deemed more suitable (Danks and Ray, 2018). The analysis of NWOM revealed that the PLS path model had a lower out-of-sample predictive error across all indicators compared to the baseline naïve LM model. Specifically, the MAE values for the PLS model were lower than those of the LM model for all NWOM indicators: NWOM_1 (PLS: 0.687 vs. LM: 0.721), NWOM_2 (PLS: 0.592 vs. LM: 0.637), NWOM_3 (PLS: 1.13 vs. LM: 1.143), and NWOM_4 (PLS: 0.92 vs. LM: 0.964). These results suggest that the model possesses strong predictive power (Shmueli *et al.*, 2019).

Mediation effect

The study introduced CIR as a mediator in the relationship between IRT barriers and NWOM. The results in Table 6 indicate that the direct effect from UB to NWOM and RB to NWOM is not significant. Therefore, we conclude that the relationship between UB and NWOM and RB and NWOM is fully mediated by CIR, supporting *H7a* and *H7c*. Additionally, the direct effect from TB to NWOM is significant. Thus, we conclude that CIR partially mediates the effect of TB on NWOM, and there may be other factors that mediate this relationship, supporting *H7d*. Finally, the direct and indirect effects from VB to NWOM and IB to NWOM are not significant. Therefore, we conclude that CIR has no mediating role in the relationship between VB and NWOM and IB and NWOM.

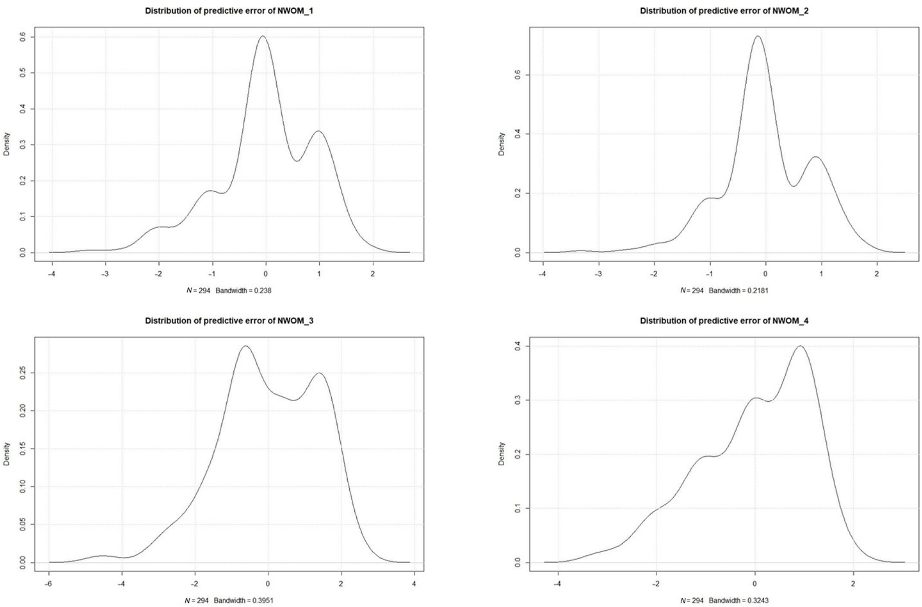

Figure 2. Distribution of prediction error

Discussion and conclusions

Discussion and conclusions

This study investigates the functional and psychological barriers contributing to CIR toward AICAs in financial services and their implications for NWOM. Grounded in Innovation Resistance Theory (IRT), the study introduces CIR as a mediator between IRT-related barriers and NWOM. The findings highlight how usage, risk and TBs influence resistance, which mediates the relationship with NWOM. The findings reveal key insights into consumer resistance in this sector.

UBs significantly and positively influence CIR. This indicates that CIR increases when chatbots are difficult to use because of inconveniences, lags and unclear steps (Yang *et al.*, 2023). These barriers align with TAM, and UTAUT emphasizes the importance of ease of use. To address this, chatbot providers must ensure transparent and readily accessible protocols for all consumers. This result is supported by the study results of Elok Behera *et al.* (2023), Chu (2023), Khanra *et al.* (2021) and Baklouti and Boukamcha (2024).

Contrary to prior studies that emphasized VBs (Behera *et al.*, 2023; Chu, 2023; Leong *et al.*, 2020, 2021), VBs had an insignificant influence on CIR. This result was presumed to be because chatbots in financial services often provide similar functionalities, are perceived as “complementary” and come with an inherent expectation of convenience, reducing the importance of value trade-offs (Jana, 2022). Immediate concerns, such as usability, trust and perceived risks, overshadow abstract evaluations of value, especially in markets such as Egypt, where trust and cultural norms heavily influence consumer behavior (Elsotouhy *et al.*, 2023; Khanra *et al.*, 2021). Providers should focus on addressing these pressing concerns, rather than solely emphasizing the chatbot’s value proposition. This finding aligns with prior studies (Jana, 2022; Khanra *et al.*, 2021; Mani and Chouk, 2018).

Table 6. Results of mediation effect

Total effects	*t*-statistics	Direct effect	*t*-statistics	Hypothesis / Relationship	Indirect effects	*t*-statistics	5% CI	95% CI	D
0.166	2.286*	0.124	1.727	*H7a*: UB → CIR → NWOM	0.043	2.018*	0.010	0.079	FM
0.137	2.266*	0.125	2.081*	*H7b*: VB→ CIR → NWOM	0.011	1.028	−0.005	0.029	NM
0.130	2.389*	0.095	1.692	*H7c*: RB → CIR → NWOM	0.034	1.991*	0.008	0.064	FM
0.219	2.786**	0.162	2.067*	*H7d*: TB→ CIR → NWOM	0.057	2.198*	0.014	0.099	PM
0.154	2.348*	0.152	2.389*	*H7e*: IM → CIR → NWOM	0.002	0.159	−0.013	0.018	NM

Note(s): UB = Usage barrier, VB = Value barrier, RB = Risk barrier, TB = Tradition barrier, IB = Image barrier, CIR = consumer innovation resistance, D = Decision, NM = no mediation, PM = partial mediation and FM = Full mediation and *p*-value (*= $p < 0.05$ and **= $p < 0.01$)

RBs, including concerns about privacy, fraud, uncertainty, chargebacks and transaction errors, significantly affect CIR. Addressing these risks through robust security measures and transparent communication is crucial for reducing consumer apprehensions (Huang *et al.*, 2021; Leong *et al.*, 2021; Xie *et al.*, 2024). This result is supported by the study results of Behera *et al.* (2023), Chu (2023) and Jana (2022) and, in contrast, with the results of Khanra *et al.* (2021).

Traditional barriers emerge as the strongest determinant of CIR. This result is supported by the study results of Behera *et al.* (2023), Leong *et al.* (2020) and Sivathanu (2019) and, in contrast, with the results of Chu (2023) and Jana (2022). These results indicate that perceptions of incompatibility with users' experiences, values, and norms–as well as the absence of human interaction–significantly contribute to CIR. Such barriers are consistent with the UTAUT, which emphasizes the role of social influences in shaping resistance. These barriers align with UTAUT, emphasizing the importance of social influences.

Surprisingly, IBs had an insignificant impact on the CIR to chatbots. This result was inconsistent with that reported by Behera *et al.* (2023), Chu (2023), Jana (2022) and Khanra *et al.* (2021) and in line with the results of Cheng *et al.* (2018) and Leong *et al.* (2020). This insignificant result can be explained by the fact that consumers have a positive impression of chatbots because of their ease of use and usefulness (aligned with the TAM and UTAUT). This positive image may be attributed to respondents' tech-savviness and their perception of chatbots aligning with their self-image (Chu, 2023). In addition, government support for financial services in the banking sector may contribute to this positive image.

Moreover, the results indicate that CIR significantly influences NWOM. This result aligns with Jana (2022), indicating that resistance, characterized by feelings of irrelevance, mistrust or perceived inefficiency, fuels NWOM behavior, which encompasses actively voicing dissatisfaction, disseminating negative remarks, participating in adverse conversations and cautioning others against availing of these services. Service providers should focus on improving chatbot relevance, usability and trustworthiness to reduce the CIR and its subsequent impact on NWOM.

The mediating analysis reveals that CIR fully mediates the effects of usage and RBs on NWOM and partially mediates the effect of TBs, suggesting that these barriers lead to resistance, which in turn drives NWOM behavior. The findings align with Jana (2022) regarding RBs but differ from those of Talwar *et al.* (2021). The variances in NWOM conduct concerning RBs can be ascribed to an amalgamation of cultural, technological, regulatory and market-specific determinants, with Egyptian consumers potentially augmenting risk tolerance or a more lenient perspective of nascent financial technologies. The partial mediation of TBs suggests the presence of additional mediators that are not captured in this study, consistent with Kaur *et al.* (2021) but differing from Jana (2022). The non-significant impact of value and IBs on NWOM may reflect that consumers do not fully perceive value trade-offs and perceive innovation as aligning with their self-image because of tech-savviness. These variations emphasize the importance of cultural and technological contexts in shaping CIR and NWOM relationships.

Theoretical implications

This study contributes to the existing literature on CIR regarding AICAs by analyzing CIR toward chatbots in the context of financial services, thereby reducing gaps in the relevant literature. This expansion enriches IRT's applicability beyond the traditional innovation context. Moreover, the current investigation extends the scope of IRT research by exploring the outcomes of CIR in the form of NWOM. This integration extends beyond traditional metrics (e.g. adoption intention, use intention or continued intention to use) and situates CIR within broader societal impacts, enriching the explanatory scope of IRT.

The mediating role of CIR between functional and psychological barriers and NWOM provides a nuanced understanding of the resistance dynamics. Usage and RBs are fully mediated by CIR, whereas TBs exhibit partial mediation, suggesting varying pathways of influence. These insights emphasize the critical role of CIRs in shaping consumer responses to innovative technologies, offering a foundation for future studies investigating the mediating and moderating roles of CIRs across different contexts.

The results revealed the limitations of TAM and UTAUT, emphasizing the need to include resistance-related factors. Barriers, such as usability issues, risk perceptions and preferences for conventional approaches, provide an alternative lens to enhance the explanatory power of these models. The integration of resistance elements may resolve conflicting outcomes in technology adoption studies and offer a balanced view of both facilitators and inhibitors.

Managerial implications

Recognizing that IRT barriers have varying influences on CIR and NWOM, financial service providers can adopt targeted, data-driven approaches to overcome these barriers. To overcome traditional barriers, service providers must position chatbots as complementary to traditional interactions, rather than substitutes (Chang and Hsiao, 2024). Personalizing AICA interactions to increase human touch can further alleviate concerns regarding impersonal interactions (Mariani *et al.*, 2023). Additionally, using hybrid service models to integrate AICA with existing customer service channels allows consumers to effortlessly transition from chatbot interactions to live-agent support, when necessary, thereby alleviating frustration and fostering positive engagement.

To address UBs, service providers should implement a user-centric design that prioritizes ease of use, clear instructions and intuitive interfaces. This could involve training programs for customers to interact with chatbots effectively and transparently to communicate their functionalities. Furthermore, addressing RBs requires proactive measures, such as robust data privacy protocols, transparent communication regarding data protection measures and clear guidelines for error resolution. These steps can mitigate privacy and security concerns and foster greater confidence in AICAs.

Despite this study's conclusion that value and IBs do not significantly impact CIR or NWOM, it remains imperative to improve consumers' perceptions of AICA in financial services. Financial service providers should carefully craft marketing campaigns that emphasize the advantages of AICA, such as convenience, time-saving and improved control over financial matters (Talwar *et al.*, 2020). Moreover, targeted campaigns should focus on showcasing successful real-life applications of chatbots in financial services to transform chatbots' perceptions from mere technological innovations to practical financial instruments, thereby underscoring their tangible value to consumers.

Given the mediating role of CIR, reducing consumer resistance can indirectly mitigate NWOM (Jana, 2022). Educational initiatives, such as interactive tutorials, comprehensive FAQs sections and user feedback mechanisms, can enhance user confidence and satisfaction. Furthermore, encouraging positive word-of-mouth through loyalty incentives and satisfied customer testimonials can counteract NWOM (Méndez-Suárez and Danvila-Del-valle, 2023).

Finally, financial service providers should adopt an agile framework for continuous monitoring and adaptation. Tools such as social listening and sentiment analysis can track real-time discussions regarding services, enabling prompt responses to user complaints and preventing negative experiences from escalating into NWOM (Talwar *et al.*, 2021). Providers should implement a dynamic strategy that adapts to evolving consumer needs and

Table 7. Conclusion and theoretical and managerial implications

Conclusion	Theoretical and managerial implications
Usage, risk, and tradition barriers significantly influence consumer resistance	Reinforce IRT's applicability to understanding resistance dynamics in financial services; Prioritize user-centric chatbot designs, emphasizing usability, security and trust; Integrate chatbots seamlessly with traditional channels
Value and image barriers do not significantly affect resistance or NWOM	Challenge assumptions about the universal applicability of value and image barriers across contexts; Shift focus to usability, trust and contextual barriers when designing chatbot strategies
Consumer resistance mediates the relationship between usage, risk and tradition barriers with NWOM	Demonstrate the mediating role of resistance, expanding IRT to include NWOM as an outcome; Address resistance through education, transparency and incentives to foster PWOM
Resistance-related NWOM can harm adoption and brand perception in financial services	Highlights the broader social consequences of resistance, linking individual barriers to collective outcomes such as NWOM; Implement social listening and rapid response mechanisms to address negative feedback effectively

expectations to sustain trust, minimize resistance and ensure the long-term success of AI-powered solutions in financial services.

Limitations and suggestions for future research

This study has a few limitations. First, it uses an IRT lens that focuses only on the barriers that influence consumer behavior. Future investigations could assess both the inhibitors and motivators of technology adoption that influence consumer resistance through frameworks such as the Behavioral Reasoning Theory, providing a more balanced view of consumer behavior. Second, this study focused on barriers specific to technological characteristics. Consumer barriers such as individual attitudes, emotions and cognitive biases can also play a significant role in shaping CRI. Future studies should integrate technological and consumer barriers into the holistic view of resistance. Third, while this study targets emerging markets, it highlights the necessity for research on the bottom of the pyramid populations, where technological access and consumer behavior may differ significantly. Exploring resistance to financial innovation among bottom of the pyramid consumers in developing contexts could offer valuable insights into affordability, trust and accessibility. Finally, this study focused on chatbots as a financial service innovation, yet other evolving financial technologies such as "buy now, pay later warrant investigation because of their potential to elicit distinct consumer resistance types". Future research could include these innovations to better understand consumers' responses.

Table 7 summarizes the study conclusion and implications.

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