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Analysis of mobile fintech adoption based onperceived value and risk theory: findings from PLSSEM and fsQCA

Md. Kaysher Hamid

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Correspondence	mkhamid21@gmail.com

KEYWORDS: fintech, theory

ABSTRACT

The rapid evolution of the financial sector, driven by fintech innovations underscores the
importance of understanding the factors influencing mobile fintech adoption, especially in
light of privacy and security concerns that hinder user acceptance. This study bridges a gap in
the existing literature by proposing an integrated model synthesising perceived value and risk
theories, offering a comprehensive framework for analysing mobile fintech adoption.
Employing a dual-method approach that integrates Partial Least Squares Structural Equation
Modelling (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA), this

study empirically investigates the interplay of various value and risk factors affecting adoption intentions among Chinese users. The PLS-SEM results reveal that the integrated model substantially enhances explanatory power, accounting for 46.27% of the variance in mobile fintech adoption. Utilitarian value, social value, performance risk, and time risk show statistically significant net effects on adoption. The fsQCA results identify seven distinct configurations associated with high-level mobile fintech adoption, and eight causal paths giving rise to its negation, highlighting the complexity of decision-making processes in this context.

These findings have significant implications for both academic discourse and practical applications, advocating for the adoption of multifactorial frameworks in future studies to enhance understanding of technology acceptance in dynamic environments.

সীমিত

(বিইউপি)

চীফ ফাইন্যান্স অফিসারের অফিস

এল এম

অতীব জরুরী

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বিইউপিতে কর্মরত সকল বেসামরিক শিক্ষক, কর্মকর্তা ও কর্মচারীদের বেতন-ভাতা হতে অগ্রিম আয়কর কর্তণ প্রসঙ্গে

বরাত:

ক। আয়কর আইন, ২০২৩।

খ। সিনিয়র সচিব, অভ্যন্তরীণ সম্পদ বিভাগ ও চেয়ারম্যান জাতীয় রাজস্ব বোর্ড, ঢাকা ডি ও পত্র নং ০৮.০১.০০০০.০৩০.০৩.০১১. ১৬/২৪১(৭০); তারিখ: ১৭ এপ্রিল ২০১৬ খ্রি:।

১। আয়কর আইন, ২০২৩ এর ৮৬ (১) ধারার বিধান অনুযায়ী বিইউপিতে কর্মরত সকল বেসামরিক শিক্ষক, কর্মকর্তা ও কর্মচারীদের (প্রযোজ্যতা অনুযায়ী) বেতন-ভাতা হতে উৎসে কর কর্তণের বিধান রয়েছে। এরই ধারাবাহিকতায় বর্তমান ২০২৫-২০২৬ অর্থবছরে বিইউপিতে কর্মরত সর্বমোট ১০১১ জন বেসামরিক শিক্ষক, কর্মকর্তা ও কর্মচারীদের মধ্যে ১২৭ জনের বেতন-ভাতা হতে উৎসে কর কর্তণ করে প্রতি মাসে উপ-কর কমিশনারের কার্যালয়, সার্কেল-২৩৮ (কোম্পানীজ), কর অঞ্চল-১১, সেগুনবাগিচা, ঢাকা বরাবর প্রেরণ করা হয়ে থাকে।

২। অত্র বিশ্ববিদ্যালয়ে কর্মরত সকল বেসামরিক শিক্ষক, কর্মকর্তা ও কর্মচারীদের ব্যক্তিগত নথি পর্যালোচনান্তে প্রতীয়মান হয় যে, বর্তমান ২০২৫-২০২৬ অর্থবছরে বিইউপিতে সর্বমোট ১০১১ জন বেসামরিক শিক্ষক, কর্মকর্তা ও কর্মচারীদের মধ্যে আয়কর পরিশোধকারী ১২৭ জন ও আয়কর প্রযোজ্য নয় ৬৮৫ জন বাদে (১০১১-১২৭-৬৭৫)=১৯৯ জনের বেতন-ভাতা বাবদ আয় হতে আয়কর প্রযোজ্য হলেও বেতন ভাতা হতে আয়কর কর্তণ করছেন না (নামীয় তালিকা সংযুক্ত)।

এমতাবস্থায়, বর্ণিত ১৯৯ জন বেসামরিক শিক্ষক, কর্মকর্তা ও কর্মচারীদের আয়কর সংক্রান্ত যাবতীয় তথ্যাদি নিম্নোক্ত ছক মোতাবেক পূরণকরত: চীফ ফাইন্যান্স অফিসারের অফিসে আগামী **৩০ অক্টোবর ২০২৫ খ্রি:** তারিখের মধ্যে প্রেরণ করার জন্যে বিশেষভাবে অনুরোধ করা হলো:

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৩। উল্লেখ্য যে, বর্ণিত ১৯৯ জন বেসামরিক শিক্ষক, কর্মকর্তা ও কর্মচারীদের মধ্যে আয়কর কর্তণের পরিমান অবগত করা না হলে অত্র অফিস কর্তৃক বিধি মোতাবেক ন্যূনতম আয়কর কর্তণপূর্বক নভেম্বর ২০২৫ খ্রি: হতে বেতন-ভাতা প্রদান করা হবে।

৪। বিষয়টি আপনাদের পরবর্তী কার্যক্রমের জন্য প্রেরণ করা হলো।

ড. মো: নকির উদ্দীন
পরিচালক (অর্থ ও হিসাব)
পক্ষে সিএফও

২৯ অক্টোবর ২০২৫ খ্রি:

বর্ধিত ১৫৭০

সংযুক্তি:
ক। বরাত 'ক' ও 'খ' এর ফটোকপি।
খ। শিক্ষক, কর্মকর্তা ও কর্মচারীদের নামীয় তালিকা (আয়কর কর্তণ করেন না)।

প্রতি:

সংশ্লিষ্ট ফ্যাকাল্টি/অফিস/বিভাগ/শাখা/সেল

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availability of sustainable products related to consumer behavior control, which implies difficulty in obtaining or consuming specific products. Consumers stated that it was difficult to purchase products because, although they had high motivation to consume eco-friendly products, these products had a low ease of use. This problem is related to the lack of retail stores or product markets that sell these products, which leads to irregularities and a lack of convenience desired by consumers.

2.3.2. Eco Label Credibility

The eco label provides identifiable marketing tools to communicate the environmentally friendly and socially desirable characteristics of a product to consumers [38]. Eco labels are known to improve consumer response to both green advertising and brands, and are considered to serve as objective guarantees for the environmental information of products. The trust in eco labels simplifies information retrieval and improves consumer decision-making. Gleim et al. [30] considered that trust is significant when considering the purchase of eco-friendly products, and a lack of trust in eco-friendly products cannot have a positive effect on eco-friendly consumers. Accordingly, it is judged that consumers' trust in eco labels as an information source significantly impacts their decision to purchase eco-friendly products.

2.4. Research Model and Hypothesis

Based on the environmental consciousness mentioned by Joshi and Rahman [7], this study aimed to examine the effects of environmental consciousness on eco-friendly product purchase intention and the adjustment effect of label credibility. The research model of this study is shown in Figure 1.

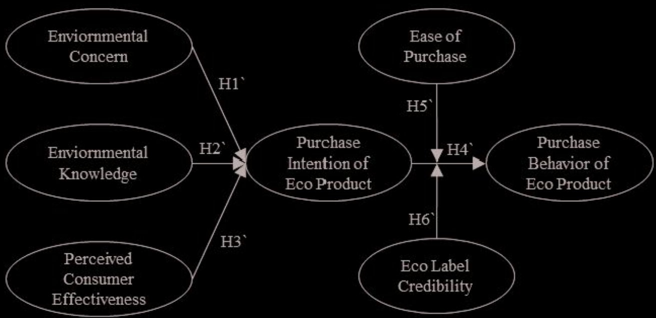

Figure 1. Research model.

2.4.1. Environmental Consciousness and Intention to Purchase Eco Products

Many of the previous literature studies have reported that the effect of environmental awareness on purchasing products, such as organic food, is insignificant, and thus the influence of environmental awareness on the intention to purchase organic food has been underestimated in the existing literature [32]. Interest was also said to be an important factor that can affect consumers' perceptions when purchasing eco-friendly products, such as organic food [39].

Environmentally conscious people often consider the environmental impact when purchasing products [35]. As such, they tend to buy organic food because they may perceive it to be safer, healthier, and less adversely impactful to the environment and eco systems [40]. Environmentally conscious consumers use more eco-friendly products than less environmentally friendly consumers [41]. Consumers' high concern in environmental and social issues and the functional and eco-friendly characteristics of products are the main motivators for inducing eco-friendly purchasing behavior [7]. Additionally, Cottrell [42] argued that environmental concerns are a reasonable predictor for environmental behavioral

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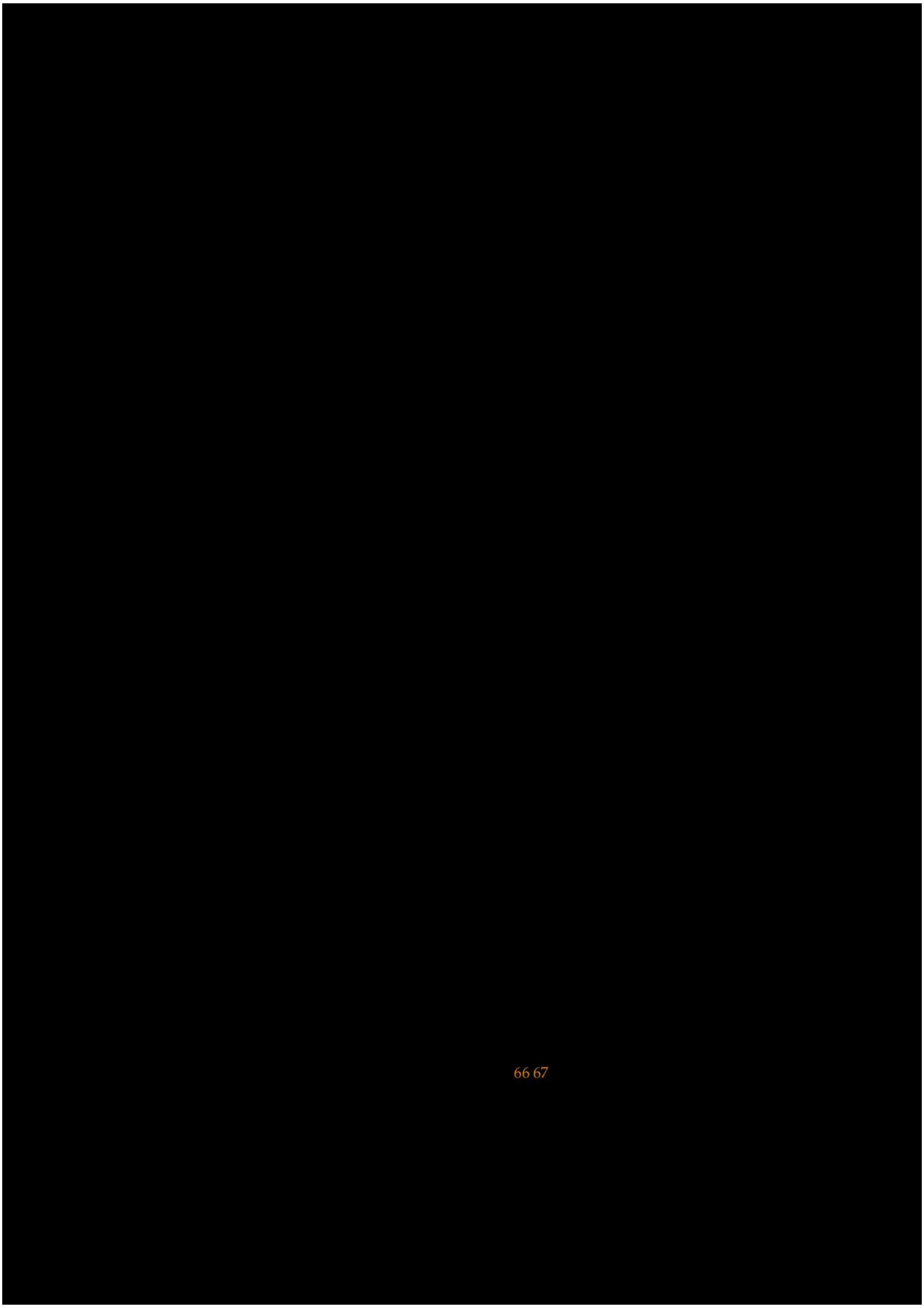
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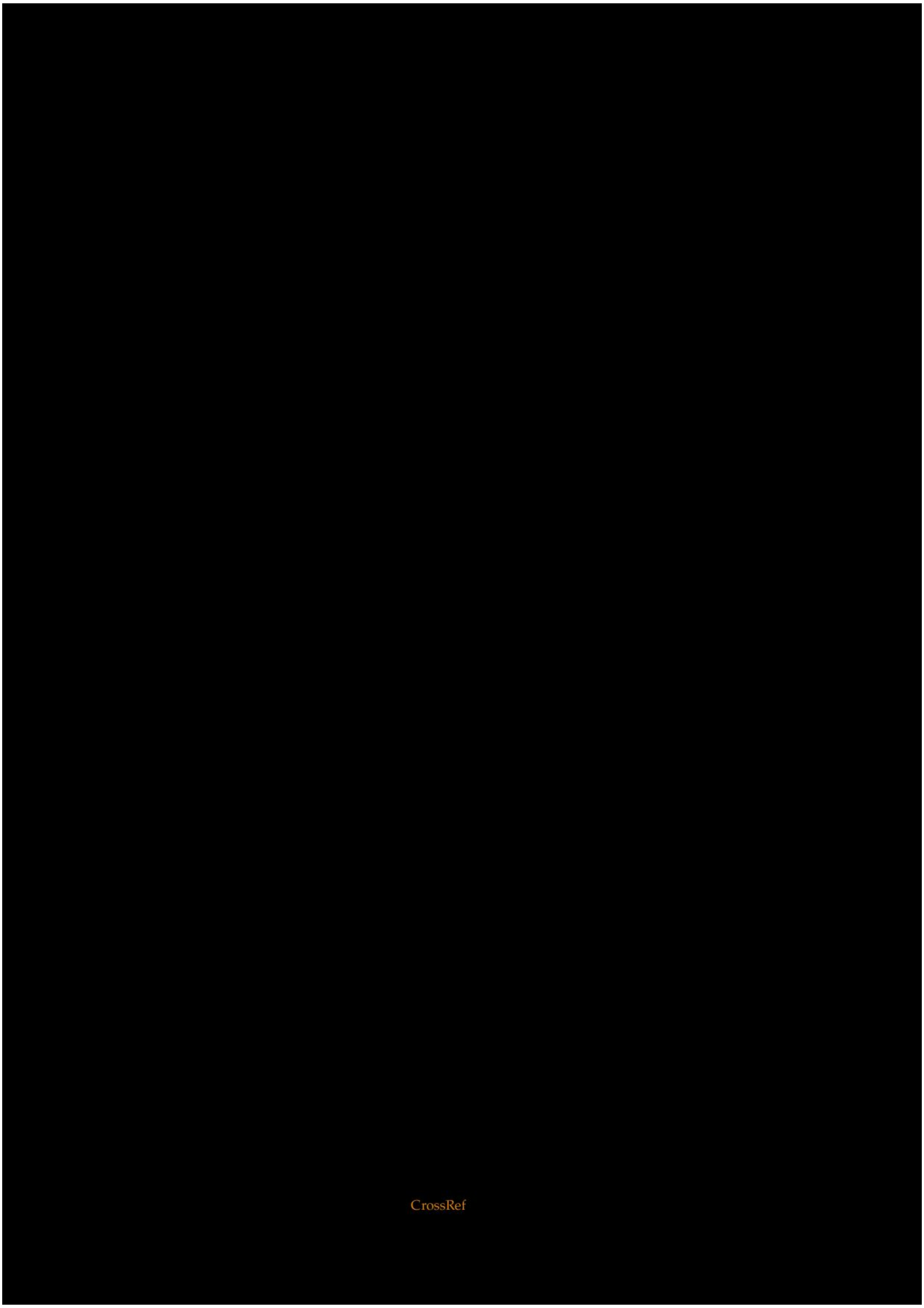
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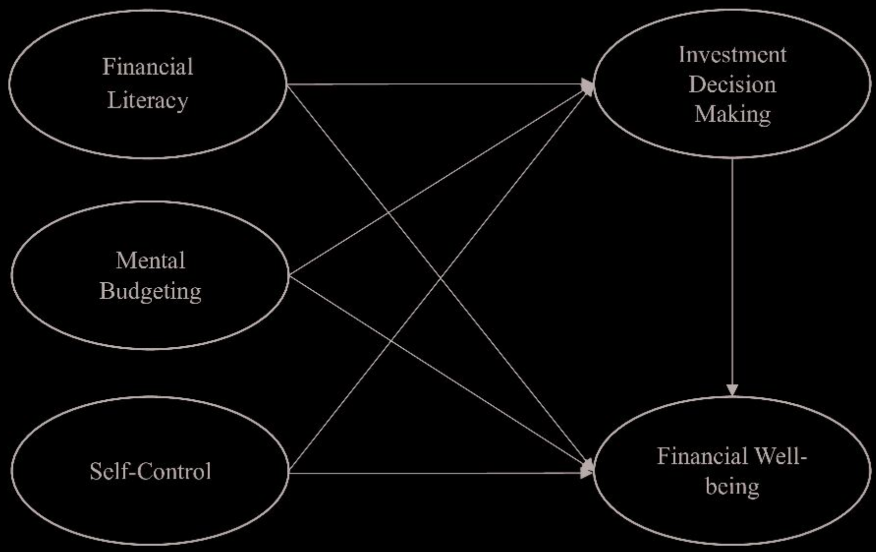

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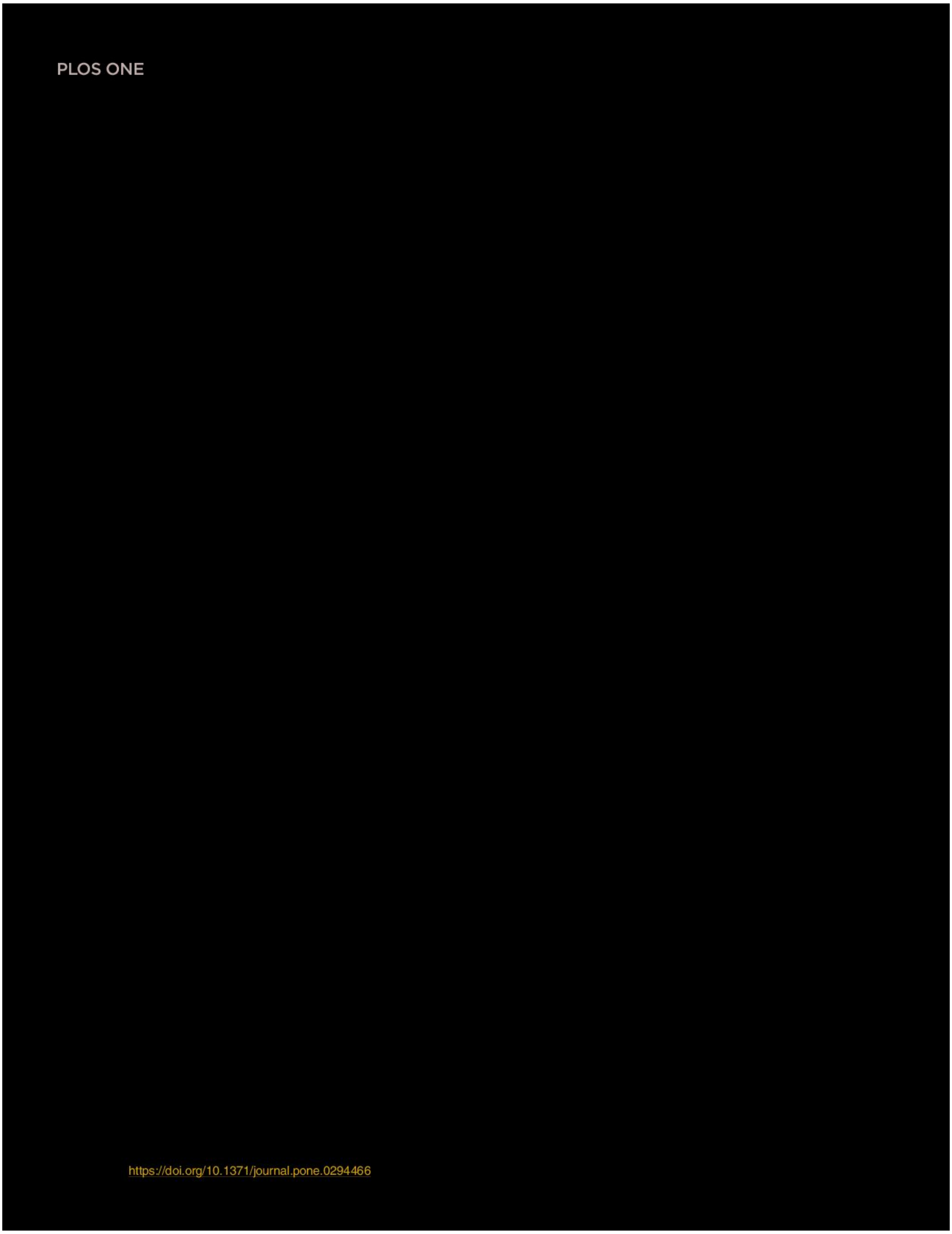
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A PLS-SEM mediation analysis of factors influencing the adoption intention of banking chatbots

Chandni, Bansal, *O.P. Jindal Global University, cbansal@jgu.edu.in*
Krishan Kumar, *O.P. Jindal Global University, kkpandey@jgu.edu.in*
Rajni Goel, *Howard University, rgoel@howard.edu*
Anuj Sharma, *O.P. Jindal Global University, anuj.sharma@jgu.edu.in*

Abstract

An important area in the field of digital financial services is the use of AI-driven banking chatbots. The growing integration of AI-driven chatbots in banking has transformed customer interaction, yet the factors influencing users' adoption intention remain underexplored, specifically understanding how post-adoption beliefs and user experiences shape behavioural intention. This study proposes a comprehensive research model which is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Expectation-Confirmation Model (ECM), and which is uniquely extended with the constructs of trust and perceived security, both crucial in high-risk, technology-mediated financial environments. The research examines the role of the mediating variables of perceived usefulness, satisfaction and trust with respect to each influencing adoption intention by utilizing the Partial Least Squares Structural Equation Modeling (PLS-SEM). Findings include that perceived usefulness mediates the effects of confirmation of expectations and perceived ease of use on adoption intention, while trust mediates the influence of confirmation of expectations, perceived usefulness, perceived security and facilitating conditions. By providing a nuanced understanding of chatbot adoption dynamics, the study advances both theory and practice. Financial institutions can successfully implement intelligent banking technologies by using the actionable insights it offers to increase user acceptance of conversational AI tools.

Keywords: banking chatbot, mediation, adoption intention, PLS-SEM, UTAUT, ECM

Introduction

Artificial intelligence (AI) and natural language processing (NLP) technologies are rapidly being adopted by a wide range of industries including the financial sector (Mah et al., 2022). A key area in the field of digital financial services is the use of AI-driven banking chatbots. Banking chatbots provide 24/7 customer service, automate routine queries which potentially can improve the overall service efficiency. Understanding the determinants that drive people to adopt chatbots has become essential for financial institutions using chatbots to improve the experiences of customers and sustain competitive advantage (Alt et al., 2021). Although banking chatbots tend to be technologically sophisticated, user adoption remains inconsistent, battling with challenges like the lack of human interaction, growing need for multilingual support, limitations in natural language processing as well as ethical challenges (Bansal et al., 2024; Bansal, 2025).

This research explores factors influencing the adoption of banking chatbots, drawing upon the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) and the Expectation-Confirmation Model (ECM) by Bhattacherjee (2001). The previous studies either focus solely on adoption or satisfaction, rarely addressing the mediating mechanisms between perceptions and behavioral intentions. Reviewing how the growing integration of AI-driven chatbots in banking has transformed customer interaction, the factors influencing users' adoption intention have surprisingly remained underexplored. For example, understanding how post-adoption beliefs and user experiences shape behavioral intention may influence chatbot adoption. As such, an integrated model is required to account for both pre-adoption expectations and post-adoption experiences, especially in AI-powered service contexts in which trust, and satisfaction play critical roles (Zahra et al., 2023). This highlights a significant theoretical gap that the present study aims to address. For the same purpose, the study proposes the following research questions:

RQ1: *What factors influence the adoption intention (ADI) of banking chatbots in India?*
RQ2: *What relationship exists between the factors (as identified in RQ1) and ADI of banking chatbots in India?*
RQ3: *Which are the factors and the nature of their mediation towards ADI of banking chatbots in India?*

The current study develops an integrated framework which utilizes the UTAUT and ECM theories to study users' adoption intentions toward banking chatbots, by employing PLS-SEM method. More specifically, UTAUT and ECM are extended with the constructs of trust and perceived security, both crucial in high-risk, technology-mediated financial environments (Trewin et al., 2016; Featherman et al., 2006). The use of PLS-SEM enables robust analysis of complex relationships, including direct, indirect, and mediated effects. Using PLS-SEM, the role of the mediating variables perceived usefulness, satisfaction, and trust with respect to adoption intention is examined. PLS-SEM is selected as it tolerates complex models involving multiple latent constructs, mediating variables, and non-normal data distributions.

The methodology steps include identifying and validating the key antecedents influencing banking chatbot adoption intentions by assessing the measurement model, ensuring that the identified constructs are reliably measured. Next, we examine the structural model in which hypothesized relationships among the constructs are empirically evaluated through path coefficients and their statistical significance. Finally, to answer research question 3, mediation analysis is performed based on the PLS-SEM framework to explore mediating effects of intermediating factors on ADI.

The study reinforces satisfaction as the central construct for technology adoption and identifies trust as a relational construct binding cognitive appraisals with behavioral outcomes in digital financial services. Research outcomes contribute to existing banking chatbot knowledge by bridging the gap between the pre-adoption and post adaption perspectives of the adoption of chatbots. Second, the framework incorporates constructs of perceived security and trust, which are typically absent from existing models, yet are highly relevant in the banking context. Third, this research transcends the conventional adoption model in terms of mediating effects of perceived usefulness, trust, and satisfaction to explain how the user perceptions significantly influence the behavioral intention to adopt. Additionally, this work looks at how chatbots might alter the way customers communicate with banks.

Literature Review and Hypotheses Development

Banking Chatbot Adoption

Recent emergence of Artificial Intelligence (AI) in the financial services industry has made chatbots very popular as a cost efficient and scalable means of customer communication (Patil & Kulkarni, 2019).

Banking chatbots are software programs that employ artificial intelligence (AI) and natural language processing (NLP) to replicate human conversation in order to assist consumers with enquiries, transactions, and account management (Bansal et al, 2023). These tools are becoming progressively popular among banks worldwide due to the fact that they can lower operating costs, offer round-the-clock support, and facilitate personalised interactions (Richad et al., 2019 & Agrawal et al., 2024). In the Indian context, it has been observed that the adoption of the chatbots has been accelerated by both the public and private sector banks over the past few years (Singh & Singh, 2019).

Although, banking chatbot has served to improve customer service and operational efficiency, its adoption is quite slow in developing economies like India (Gupta & Sharma 2019; Rani et al 2023). Some users remain reluctant to these technologies given a lack of trust, usability problems or negligible human support (Bansal et al. 2024, Hari et al., 2022), causing variability in user acceptance. Studies on banking chatbots have primarily aimed to identify factors influencing user acceptance or rejection. Table 1 presents important studies regarding banking chatbots.

Table 1. Studies on Banking Chatbots

Country	Theoretical Underpinning	Data Analysis Technique	Aim of the study	Reference
India	SEM	IS Success Model	The study looks into how the three key quality aspects of the ISS Model are connected to customers' overall experience	Trivedi (2019)
Indonesia	TAM	PLS-SEM	To study the enablers influencing operations of banking chatbot in Indonesia, focussing on millennials	Richad et al. (2019)
Romania	TAM	PLS-SEM	To study the enablers influencing operations of banking chatbot in Romania	Alt et al. (2021)
India, USA, and Singapore	UTAUT2, BDI	PLS-SEM	To investigate how human needs and beliefs affect the use of fintech chatbots	Sugumar & Chandra (2021)
Turkey	ECM	PLS-SEM	The study investigates how customer satisfaction is impacted by perceived trust and the bank's reputation.	Eren (2021)
Vietnam	ECM, D&M ISS	SEM	To study the enablers influencing users' decisions to continue utilizing chatbot services in Vietnamese banking industry	Nguyen et al. (2021)
Vietnam	NA	Regression Analysis	To investigate the ways in which users' willingness to share personal information is influenced by trust and privacy concerns in relation to the Vietnamese banking industry	Lappeman et al. (2022)
India	TAM	SEM	To identify the elements that contribute to and influence customer brand interaction with banking chatbots	Hari et al. (2022)
Norway	NA	Thematic analysis	To investigate the elements that affect consumers' interactions with banking chatbots, with an emphasis on both chatbot-related and user-related elements	Petersson et al. (2023)

Theoretical Underpinning

The current study builds on the insights from well-known models that explain how people adopt and use technology. The Unified Theory of Acceptance and Use of Technology (UTAUT) merges eight previous models about adopting technology and outlines four important aspects that control users' intention to use it. The UTAUT model has been widely used to understand how people interact with various information systems, such as mobile banking and digital platforms (Sarfaraz, 2017; Purwanto and Loisa, 2020; Chen et al., 2023). The Expectation Confirmation Model (ECM) is a model about post-adoption that examines how users continue to use a product by comparing their experience with what they expected and their satisfaction.

Previously, researchers studied consumer intent and adoption of technology using UTAUT and ECM by focusing on domains such as mobile banking (Wang, 2018), mobile payment (Zhao & Bacao, 2020; Singh, 2020), e-democracy (Huda & Amin, 2023), educational chatbots (Tian et al., 2024; Aldulaimi et al., 2024), online food delivery (Subhan et al., 2024; Zhao & Bacao, 2020), social networking (Su & Tong, 2021), mobile health (Tian and Wu, 2022). Integration of UTAUT and ECM enhances insights regarding pre-adoption beliefs (e.g., ease of use, facilitating conditions) as well as post adoption evaluation (e.g., confirmation, satisfaction). One of the advantages of this hybrid approach is that it seems quite suitable for the banking chatbot settings as user experiences here evolves over time and is determined not only by technical performance but also emotional responses such as trust and satisfaction. Table 2 provides a list of studies utilizing UTAUT and ECM to explore chatbot usage and adoption.

Table 2. UTAUT + ECM Studies

Domain	Country	Data Analysis Technique	Aim of the Study	Reference
QR Code Mobile Payment Service	Indonesia	PLS-SEM	To figure out what drives people to keep using mobile payments made through QR codes	Ifada & Abidin (2022)
Mobile Payment	India	PLS-SEM	To explore how people behave after they've started using mobile payment systems	Singh (2020)
e-learning tools	Malaysia	SEM	To understand the student's intention towards PADLET as e-learning tool	Mohamad et al. (2024)
Educational Chatbots	China	PLS-SEM	To determine what aspects of AI chatbots affect students' opinions, levels of satisfaction, and behavioural intentions	Tian et al. (2024)
Online Food Delivery	Indonesia	PLS-SEM	To figure out what factors drives customers to keep using online food delivery services	Al-Rikabi et al. (2024)
Mobile Learning	Iraq	PLS-SEM	Analyses how mobile learning is being introduced and used over time in universities across Iraq	Su & Tong (2021)
Mobile Health	China	SEM	To explore whether older adults living with chronic illnesses plan to keep using mobile health (mHealth) tools	Tian and Wu (2022)
e-democracy	Indonesia	PLS-SEM	To examine the important variables affecting Indonesia's adoption of e-democracy	Huda & Amin (2023)
AI-Powered Chatbots in Higher Education	Kingdom of Bahrain	Correlation and Regression Analysis	To understand what helps or hinders the use of chatbots in colleges and universities	Aldulaimi et al. (2024)

Most of the existing research employs single theory models, lacking an integrated holistic psychological, behaviour, and experiential approach to the adoption. For example, trust and security are factors critical in financial services in which users interact with automated systems involving sensitive personal and financial information, and these not have not be considered in the models.

To provide some background, *trust* has been found to be a predictor of deployment in AI based systems and digital banking environments where human agent interaction is replaced by automation (Hildebrand & Bergner, 2021; Lui & Lamb, 2018) and trust eased uncertainty and encouraged confidence in robot generated responses, determining favourable engagement (Nordheim et al., 2019). Additionally, *security* concerns have been identified as a barrier to the successful implementation of online and mobile banking (Hanif & Lallie, 2021; Bamoriya & Singh, 2012). For a user to feel at ease and comfortable while chatting with a chatbot, they need to be sure their personal data is secure, as well as free from any possibility of fraud or unauthorized access. The included security variable has been shown to play a substantial role in shaping both trust and adoption intention (Gupta & Hakhu, 2021, Chawla et al., 2023) and adds to the explanatory power of adoption models in contexts of digital banking characterized by high risk. We combine and extend the UTAUT and ECM frameworks with constructs of trust and perceived security as additional constructs to address the risk and reliability issues faced in chatbot based banking services. A large gap is present in the literature where many of the mediating mechanisms between user perception and their adoption intention, particularly trust and satisfaction, are rarely mentioned. The present study covers this gap by integrating and comprehensively looking at both cognitive and emotional factors impacting chatbot adoption.

Factors Affecting Banking Chatbot Adoption

Though factors affecting adoption of technology have been studied, our work further connects key factors, such as confirmation of expectations, utility, user-friendliness, security, trust, facilitating conditions, and satisfaction to adoption intention, along with factors of trust, usefulness, and satisfaction acting as mediators. Below details the set of hypotheses relating these factors, which assist in addressing research question of *what relationship exists between* the factors that influence the adoption intention (ADI) of banking chatbots in India. Confirmation of Expectations (COEX) defines how closely a users' actual experience matches his or her initial expectations (Bhattacherjee, 2001). Liao et al. (2009) suggests that when technological services meet or exceed user expectations, responsiveness and service utility, users are more likely to perceive them positively. Several studies support this relationship. For example, Lee (2010) found that expectation fulfilment significantly influenced usefulness in e-learning environments. Furthermore, Obeid et al. (2024) also observed that as users' expectations of mobile banking services are satisfied, this positively influences trust in the system. In chatbot contexts, Diederich et al. (2022) found that positive confirmation of conversational agent performance resulted in more favourable evaluations and engagement. So, in light of this, the proposed hypotheses are:

> **H1***: "Confirmation of Expectations positively influences Perceived Usefulness for banking chatbot adoption."*
> **H2***: "Confirmation of Expectations positively influences Trust for banking chatbot adoption."*

Perceived Usefulness (PU) is a measure of how much a user thinks that technology can increase their efficiency (Davis, 1989). Studies have shown that PU plays a key role in shaping people's decisions whether or not to continue using a certain technology (Chaves and Gerosa, 2020; Brandtzaeg and Følstad, 2018). For banks, analysis of PU determines whether users experience more convenience, speed and efficiency with banking through chatbots. We believe that PU plays an intermediary role in the relationships between expectation fulfilment, ease of use and the constructs like trust, satisfaction and intention to adopt.

Therefore, the suggested hypotheses are:

H3: *"Perceived Usefulness positively influences Trust for banking chatbot adoption."*
H4: *"Perceived Usefulness positively influences Satisfaction for banking chatbot adoption."*
H5: *"Perceived Usefulness positively influences Adoption Intention of banking chatbot."*

Perceived Ease of Use (PEOU) is about how much someone feels that using a particular system will be simple and won't require extra mental or physical effort. PEOU has consistently been shown to impact PU, with users more likely to see a system as useful if it is also easy to use (Davis, 1989; Venkatesh & Davis, 2000). For banking chatbots, this relationship is highly relevant given their need to simplify often complex banking tasks through conversational interfaces. This means that if users find the chatbot easy to communicate with their special capabilities like natural language processing, intuitive navigation and accurate response, they are more apt to consider the chatbot as beneficial. Several studies validate this relationship (Roca et al., 2006; Gefen & Straub, 2000). Relative to chatbots, Diederich et al. (2022) highlighted that the usability and interface simplicity plays a significant role in shaping user experience as well as valuation perception of the technology. Therefore, the hypotheses presented are:

H6: *"Perceived Ease of Use positively influences Perceived Usefulness for banking chatbot adoption."*
H7: *"Perceived Ease of Use positively influences Satisfaction for banking chatbot adoption."*

Perceived Security (PS) describes the level of assurance someone has that a tech system such as a banking chatbot, protects their personal and financial data from unauthorized activities like hacking, fraud and data leaks. There has been numerous studies that support the importance of perceived security in the acceptance of technology, especially when financial transactions are involved (Tsai et al., 2022). Zhou (2011) also finds that perceived security has a strong influence on trust in case of mobile banking apps and that users must feel secure before they can trust a system. Likewise, Almaiah et al. (2022) and Siagian et al. (2022) demonstrated that perceived security directly affects trust and adoption intention in e-payment systems, where data protection concerns have a significant influence on how users perceive the application. In chatbot-enabled banking, users often share personal details and perform financial operations through conversational interfaces. Users will have more trust in the chatbot and be more satisfied if they perceive that these interactions are secure. It's especially relevant for economies like India, where digital technology adoption is rising but privacy and cybersecurity concerns are high. Accordingly, the following hypotheses are examined in the study:

H8: *"Perceived Security positively influences Trust for banking chatbot adoption."*
H9: *"Perceived Security positively influences Satisfaction for banking chatbot adoption."*

Facilitating Conditions (FC) refers to the extent to which users feel their needs are being met by the technology and assistance offered by the organization (Venkatesh et al., 2003). This means people use compatible devices, have a stable internet connection and can contact customer support when facing issues with a chatbot for banking. If the conditions are facilitated, people find it easier to adopt the new technology which adds to their confidence and improves their trust and satisfaction. Various studies have helped confirm these findings. Lu et al. (2005) discovered that positive conditions help users in becoming trusting and keen on using wireless Internet services. Similarly, Alalwan et al. (2018) reported that greater support for mobile banking leads to higher satisfaction with the bank. This is especially pertinent for banking chatbots where most users, especially first-time users or less tech savvy segment, require guidance and resources to be able to make use of the service. Hence the subsequent hypotheses are suggested:

H10: *"Facilitating Conditions positively influences Trust for banking chatbot adoption."*

H11: *"Facilitating Conditions positively influences Satisfaction for banking chatbot adoption."*

Trust (TRU) in banking chatbots means the user trusts the chatbot to be reliable, safe, transparent and not misusing their confidential details (Gefen et al., 2003). Many experts agree that trust plays a crucial role in making people adopt online systems for sensitive transactions (Okello & Ntayi, 2020). As credited by Gefen et al. (2003) and Kim et al. (2009), trust has been recognized as a key factor for bridging the gap between users' perception and their behavior (i.e., satisfaction / continued use). In case of banking chatbots, where users interact with an AI rather than a human, trust establishment is even more essential. Moreover, trust has been shown to be directly associated with both satisfaction and behavioural intention in several studies (Liang et al., 2018; Sharma & Sharma, 2019). A trustworthy chatbot decreases the perceived risk, increases user comfort, and positively affects evaluations and willingness to continuously use it. Accordingly, the subsequent hypotheses are suggested:

H12: *"Trust positively influences Satisfaction for banking chatbot adoption."*
H13: *"Trust positively influences Adoption Intention of banking chatbot."*

Satisfaction (SAT) is a user's overall affective evaluation of his or her experience with a system based on how well or poorly it meets or exceeds expectations (Bhattacherjee, 2001). In the case of banking chatbots, satisfaction is shaped by how well the chatbot performs in terms of usability, usefulness, reliability, and responsiveness during financial interactions. In service industry, satisfaction emerges when users feel that the service is not only functional but also reliable, secure, and aligned with their expectations. Satisfaction integrates multiple constructs (including PU, TRU, PEOU, PS and FC), whereby acting as a consolidated outcome of those perceptions and a precursor to adoption intention. Drawing from these insights, here are the hypotheses we're putting forward:

H14: *"Satisfaction positively influences Adoption Intention of banking chatbot."*

Figure 1 illustrates the comprehensive conceptual model, with proposed hypotheses, that connects key constructs, such as COEX, PU, PEOU, PS, TRU, FC, and SAT to ADI, with TRU, PU, and SAT acting as mediators. This model forms the foundation for empirical testing using PLS-SEM.

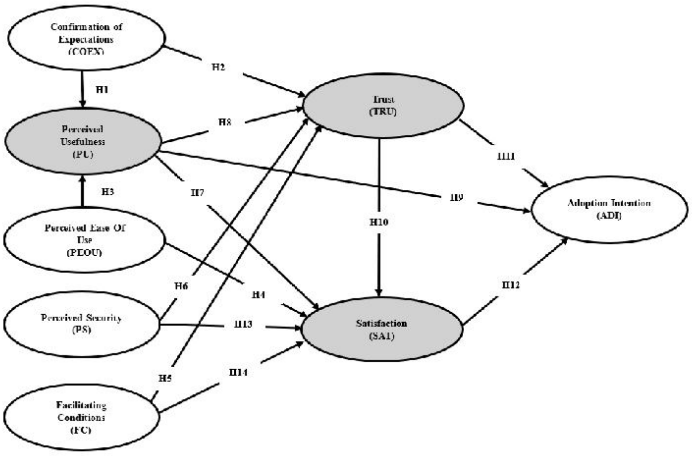

Figure1. Conceptual Research Model

Research Methodology

The current research focuses on banking customers in India as its target group, who have prior experience interacting with banking chatbots, either through mobile banking apps, websites, or social media platforms. Given the increasing use of digital banking tools in urban and semi-urban India, the study employed purposive sampling technique, ensuring that only relevant respondents with actual chatbot interaction experience were included. We gathered the data through an online questionnaire that people filled out themselves. It was shared through email, social media, and online banking forums to reach a wide range of participants. Screening questions were used to confirm respondents' eligibility based on their prior use of banking chatbots.

The study collected 552 responses and 355 of them were used after data cleaning. From Davis (1989), items for PU and PEOU were adopted, whilst COEX and SAT were drawn from the ECM Model by Bhattacherjee (2001). Other items such as TRU and PS were sourced from studies on digital banking and e-commerce adoption (e.g., Gefen et al., 2003; Pavlou, 2003). Measures of FC were based on UTAUT model (Venkatesh et al., 2003).

Common Method Bias
Since the data for both main and secondary variables came from the same survey, the possibility of Common method bias (CMB) should be considered. If errors occur in the measurement of CMB data, it may cause researchers to overestimate the relationships and alter their findings (Podsakoff et al., 2003). This study uses Kock's VIF criterion and Harman's single factor test for detecting common method bias. Exploratory Factor analysis (EFA) was performed on all eight constructs without rotation. According to Harman's test, no prominent common method bias was present in the data set since all cumulative loading accounts for only 26.57 percent of the variance, which is far below the 50 percent limit (Podskoff et al., 2003). Furthermore, according to Kock (2015), common method variance is no problem in the current dataset as VIF results (1.541 to 2.782) are lower than the acceptable threshold of 3.3.

Data Analysis and Findings of the Study

This study relied on Smart PLS 4.0 because it is the most trusted technique for analysing statistical results in information systems studies (Eren, 2021; Hari et al., 2022). The PLS-SEM analysis in this study is carried out through the following phases:

Measurement Model Analysis
To ascertain the reliability and validity of the study, a PLS SEM measurement model is evaluated to determine the optimal facets for the measurement of the latent constructs. Hair et al. (2019) guidelines were followed for evaluation of all the parameters. Outer loadings were first used to assess indicator reliability with all items exceeding the recommended threshold of 0.70.

To demonstrate acceptable reliability, Cronbach's Alpha and Composite Reliability (CR) were used and all values were above 0.70 minimum criterion values, which means that indicators were consistently representing their respective constructs. Average Variance Extracted (AVE) was calculated for each construct and all AVE values were above 0.5, indicating acceptable convergent validity. Table 3 below summarises the results of above analysis.

Table 3. Measurement Model Analysis

Constructs	Items	Factor Loading	Cronbach's alpha	Composite Reliability	AVE
COEX	COEX1	0.717	0.723	0.840	0.638
	COEX2	0.884			
	COEX3	0.787			
PU	PU1	0.808	0.769	0.853	0.592
	PU2	0.792			
	PU3	0.746			
	PU4	0.729			
PEOU	PEOU1	0.714	0.814	0.878	0.643
	PEOU2	0.815			
	PEOU3	0.884			
	PEOU4	0.786			
PS	PS1	0.742	0.760	0.760	0.579
	PS2	0.767			
	PS3	0.746			
	PS4	0.786			
FC	FC1	0.818	0.579	0.858	0.602
	FC2	0.740			
	FC3	0.811			
	FC4	0.731			
TRU	TRU1	0.700	0.752	0.842	0.573
	TRU2	0.724			
	TRU3	0.818			
	TRU4	0.779			
SAT	SAT1	0.809	0.821	0.882	0.651
	SAT2	0.788			
	SAT3	0.848			
	SAT4	0.780			
ADI	ADI1	0.865	0.877	0.916	0.730
	ADI2	0.874			
	ADI3	0.833			
	ADI4	0.845			

To ensure the dimensions are not biased, we used both Fornell-Larcker Criterion (Fornell & Larcker 1981) and the Heterotrait-Monotrait Ratio (HTMT) and the results are shown in Table 4.

Table 4. Discriminant Validity

"Fornell-Larcker Criterion"

Variables	FC	SAT	ADI	COEX	PEOU	PU	TRU	PS
FC	0.761							
SAT	0.241	0.807						
ADI	0.175	0.355	0.855					
COEX	0.356	0.161	0.230	0.799				
PEOU	-0.096	0.069	-0.127	-0.193	0.802			
PU	0.446	0.200	0.290	0.528	-0.242	0.769		
TRU	0.397	0.387	0.731	0.467	-0.269	0.540	0.757	
PS	0.405	0.378	0.280	0.346	-0.175	0.503	0.417	0.776

“HTMT Criterion”							
FC							
SAT	0.299						
ADI	0.207	0.409					
COEX	0.460	0.210	0.267				
PEOU	0.155	0.099	0.147	0.267			
PU	0.557	0.246	0.352	0.677	0.298		
TRU	0.530	0.475	0.861	0.624	0.352	0.736	
PS	0.502	0.462	0.339	0.440	0.226	0.657	0.560

Structural Model Analysis

The overall findings of the measurement model analysis prove that the instrument is reliable and suitable for assessing the structural model. With the validation of the measurement model, the next step is to evaluate the theory by looking at the relationships between the latent constructs proposed in the structural model. Path coefficients, t-values, p-values, R^2, Q2 and effect sizes were the main indicators for reviewing the structural model. The bootstrapping method with 5,000 subsamples was used to see if each hypothesized path discovered was statistically significant. Majority of the expected relationships survived statistical testing ($p < 0.05$) and are consistent with the model. A value of 0.556 for R^2 for adoption intention suggests that the model covers a significant part of the reasons behind users' intention to use banking chatbots. Furthermore, the contribution of each exogenous variable to the R^2 value of the endogenous constructs was ascertained by analysing effect size (f^2) values, with values for SAT (0.013), PU (0.034), and TRU (0.854), indicating small to medium effects, aligning with Cohen's (1988) guidelines. Predictive relevance (Q^2) quantifies a model's ability to forecast endogenous construct values. In the current study, value of Q^2 for SAT (0.149), ADI (0.076), PU (0.279), and TRU (0.303), were all larger than zero, demonstrating predictive relevance. The summary of the structural model analysis is shown in Table 5.

Table 5. Structural Model Analysis

Hypothesis	Paths	Original Sample	Sample Mean	STDEV	t-values	P values (<0.05)
H1	COEX → PU	0.499***	0.501	0.056	8.887	0.000
H2	COEX → TRU	0.214***	0.215	0.052	4.095	0.000
H3	PU → TRU	0.299***	0.297	0.062	4.812	0.000
H4	PU → SAT	0.121*	0.121	0.060	2.019	0.043
H5	PU → ADI	0.147**	0.148	0.047	3.104	0.002
H6	PEOU → PU	0.146**	0.150	0.055	2.660	0.008
H7	PEOU → SAT	0.194***	0.195	0.047	4.096	0.000
H8	PS → TRU	0.139**	0.140	0.049	2.818	0.005
H9	PS → SAT	0.304***	0.305	0.053	5.692	0.000
H10	FC → TRU	0.131*	0.134	0.052	2.513	0.012
H11	FC → SAT	0.048	0.050	0.056	0.855	0.393
H12	TRU → SAT	0.359***	0.360	0.057	6.244	0.000
H13	TRU → ADI	0.778***	0.781	0.034	22.995	0.000
H14	SAT → ADI	0.083*	0.082	0.036	2.310	0.021

*p < 0.05, **p < 0.01, *** p < 0.001

Taken together, these findings show that the structural model is solid and reliable, the hypothesized relationships are supported, and the extended UTAUT + ECM framework effectively captures the factors driving the adoption intention of banking chatbots.

Mediation Analysis

In PLS-SEM, mediation analysis is used to find out if an independent variable indirectly influences a dependent variable by way of one or more mediator variables. In such situations, mediation is useful to observe the contributing pathways or mechanisms through which a predictor might act on an outcome, contributing to a deeper knowledge of the relationships between constructs. More precisely, the flexibility of complicated models, non-normal data, and small to medium sample sizes make PLS-SEM especially well-suited for the mediation study (Hair et al., 2019). The process generally involves estimating the effects – direct, indirect and the total effect. To ascertain if the indirect effects were statistically significant, 5,000 resamples were used in the bootstrapping process. There are 20 different significant specific indirect paths that originate from different constructs and lead to ADI, as shown in Table 6.

Table 6. Significant Specific Indirect Paths Between Constructs

Code of Path	No. of Mediators	Specific indirect paths	Original sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T values
CP1	1	FC -> SAT -> ADI	0.004	0.004	0.005	0.763
CP2	1	FC -> TRU -> ADI	0.102	0.104	0.04	2.523
CP3	1	PEOU -> PU -> ADI	0.021	0.022	0.011	1.908
CP4	1	PEOU -> SAT -> ADI	0.016	0.016	0.008	1.929
CP5	1	PU -> SAT -> ADI	-0.010	-0.010	0.007	1.47
CP6	1	PU -> TRU -> ADI	0.232	0.232	0.051	4.532
CP7	1	TRU -> SAT -> ADI	0.030	0.030	0.014	2.083
CP8	1	PS -> SAT -> ADI	0.025	0.025	0.012	2.108
CP9	1	PS -> TRU -> ADI	0.108	0.109	0.039	2.779
CP10	1	COEX -> TRU -> ADI	0.167	0.168	0.041	4.087
CP11	2	COEX -> TRU -> SAT -> ADI	0.006	0.006	0.004	1.816
CP12	2	COEX -> PU -> SAT -> ADI	-0.005	-0.005	0.004	1.412
CP13	2	COEX -> PU -> TRU -> ADI	0.116	0.116	0.028	4.117
CP14	2	PS -> TRU -> SAT -> ADI	0.004	0.004	0.002	1.666
CP15	2	PU -> TRU -> SAT -> ADI	0.009	0.009	0.005	1.807
CP16	2	FC -> TRU -> SAT -> ADI	0.004	0.004	0.003	1.448
CP17	2	PEOU -> PU -> SAT -> ADI	0.001	0.001	0.001	1.239
CP18	2	PEOU -> PU -> TRU -> ADI	-0.034	-0.035	0.017	2.053
CP19	3	PEOU -> PU -> TRU -> SAT -> ADI	-0.001	-0.001	0.001	1.331
CP20	3	COEX -> PU -> TRU -> SAT -> ADI	0.004	0.004	0.003	1.768

- In the relation between FC -> ADI, the difference between the mediating effect of SAT (CP1) and TRU (CP2) was found to be 0.098, indicating that TRU has a more substantial mediating effect than SAT.
- The mediating effect in the relation PEOU -> ADI is examined where the difference between the mediating effect of PU (CP3) and SAT (CP4) was found to be 0.005, indicating that PU has a more substantial mediating effect than SAT.

- In the relation between PU -> ADI, the difference between the mediating effect of SAT (CP5) and TRU (CP6) was found to be 0.242, indicating that TRU has a more substantial mediating effect than SAT.
- CP7 shows that SAT significantly mediates between TRU and ADI.
- CP8 and CP9 show that the difference between SAT and TRU's mediating effect in the relationship between PS-> ADI is 0.083, indicating that TRU has a more substantial mediating effect than SAT in PS -> ADI.
- CP10 shows that TRU has a significant mediating effect between COEX and ADI.
- When three paths between COEX and ADI with two mediators, showing serial mediating effects, were compared, CP13 had the strongest, and CP12 had the weakest effects. The difference between CP13 and CP12 is the largest (0.121). When differences among the path coefficients are reported in descending order individually, CP13-CP12 (0.121) > CP13-CP11 (0.110) > CP11-CP12 (0.011).
- When two paths between PEOU and ADI, with two mediators showing serial mediating effects, were compared, CP17 was more potent, and CP18 had a weaker effect. For the relation PEOU->ADI mediated by three serial mediators (PEOU -> PU -> TRU -> SAT -> ADI), the path coefficient is shown by CP19 (-0.001).
- For COEX-> ADI mediated by three serial mediators (COEX -> PU -> TRU -> SAT -> ADI), the path coefficient is shown by CP20 (0.004).

Taken together, these results reinforce the crucial mediating role PU, TRU, and SAT play in shaping users' adoption intention. However, trust consistently has been identified as a central bridge between cognitive evaluation (usefulness, security, support) and emotional responses (satisfaction), which highlights its importance in the adaption of technologies in sensitive domains like banking.

Mediation Analysis using VAF (Variance Accounted For) Value

The degree to which a mediator variable (MV) explains the relationship between an independent variable (IV) and a dependent variable (DV) is subsequently ascertained using variance accounted for (VAF). The percentage of the whole effect (direct + indirect) that may be accounted for by the mediator variable is represented by VAF. Under this method we compute the direct effect, indirect effect, and total effect, when a mediator is incorporated into the model. Interpretation: If VAF > 0.8, complete mediation exists (most of the effect is mediated); if 0.2 < VAF ≤ 0.8%, partial mediation exists (the mediator partially explains the relationship) and if VAF ≤ 0.2, mediation is insignificant (the relationship is primarily direct). Table 7 shows the independent variables' direct, indirect and total effect on the dependent variables through their mediating constructs.

Table 7. Mediation Analysis (VAF Value)

Mediation Path	Direct Effect	Indirect Effect	Total Effect	VAF	Inference
COEX->PU->TRU	0.214	0.149	0.363	0.410	Mediation in Partial
PU->TRU->ADI	0.147	0.233	0.380	0.613	Mediation in Partial
PU->TRU->SAT	0.121	0.107	0.228	0.470	Mediation in Partial
FC>TRU->SAT	0.048	0.047	0.095	0.495	Mediation in Partial
TRU->SAT->ADI	0.778	0.030	0.808	0.036	No Mediation
PU->SAT->ADI	0.063	0.010	0.157	0.064	No Mediation
PS->TRU->SAT	0.304	0.050	0.354	0.141	No Mediation
PEOU->PU->SAT	0.194	0.018	0.212	0.083	No Mediation

With a VAF of 0.410, the results show that PU partially mediates the relationship between COEX and TRU, indicating that users' perceived usefulness of the chatbot is a significant cognitive link that reinforces trust when expectations are met. With a strong VAF of 0.613, TRU is found to partially mediate the impact of PU on ADI, underscoring that while users may find the chatbot useful, it is their trust in the system that ultimately consolidates their intent to adopt. Similarly, the analysis shows that trust also plays a partial role in linking PU to SAT (VAF = 0.470), highlighting trust's emotional and relational influence in shaping users' satisfaction beyond perceived utility. Furthermore, TRU partially mediates the impact of FC on SAT (VAF = 0.495), suggesting that adequate support infrastructure contributes to satisfaction primarily by enhancing trust in the system's reliability and serviceability.

Discussion and Conclusion

This study highlights the relationships among the determinants of users' intention to use banking chatbots by blending the UTAUT and the ECM models, extending them with two key constructs: trust and perceived security, both crucial in high-risk, technology-mediated financial environments. Using PLS-SEM, this research achieved three set-out objectives: identified the factors influencing the intention to adopt, tested structural relationships between different factors, and determined the mediating roles of PU, SAT, and TRU in the structural relations between factors. Consequently, the results of the measurement model showed strong reliability and validity, and the structural model showed several significant direct effects. The mediation analysis uncovered how user perceptions are translated into behavioral intentions. Findings indicate that the influence of both PEOU and COEX on ADI was significantly mediated by PU. This implies that if users think the chatbot is easy to use and their expectations are met, the chatbot is perceived as useful, and they are more likely to adopt it.

SAT is also identified as a major finding highlighting its significance in mediating the model. More specifically, SAT fully mediates the influence of PEOU, PS and FC on adoption intention. This suggests that even if users believe the chatbot is easy to use, secure and technically well supported, such perceptions are not sufficient to directly lead to adoption. Instead, they influence satisfaction, which drives intentions to adopt. Eventually, it highlights the necessity of making sure that users are both content and positively evaluated about their experience, before they would develop a behavioral intention to use it again. According to the findings, SAT partly mediates the effects of PU and TRU on ADI. Both constructs have a direct effect on adoption, yet a large share of their effects are channelled through user satisfaction. It means that users adopt a chatbot not only because they find it useful but also because the usefulness links to trust in the system's capabilities and reliability.

The research also found TRU acting as a complete mediating factor that links COEX, PS and FC to ADI. This implies that while certain expectations of users can be met or users can perceive a system as being secure and supported, neither of these alone will necessarily affect users' intentions to adopt. Instead, they operate by enhancing trust, which in turn drives adoption. This highlights the importance of trust building mechanisms like transparency, consistent performance, and reliability in accomplishing the design and deployment of the chatbots in banking sector. In addition, TRU is discovered to mediate the relationship between PU and ADI partially. This means people are willing to adopt banking chatbots not merely because they are useful, but because the usefulness instils trust in the system's capabilities and reliability.

This study highlights the multi-dimensional nature of technology adoption in sensitive areas like banking where a wrong decision may result in significant economic loss. Technology adoption does not depend solely on the utility of the system or system features but is instead a combination of cognitive evaluation (usefulness, confirmation) and affective responses (satisfaction, trust), with mediating constructs acting as important medium for linking the technical attributes to the behavioral outcomes. While prior studies often found a direct link between some other factors like support infrastructure and digital literacy with satisfaction, our findings suggest that in the case of banking chatbots, users may value support features more for building trust than for generating immediate satisfaction. This indicates that trust acts as a necessary emotional filter, through which facilitating conditions influence user satisfaction indirectly.

The results provide banks and financial service providers with useful suggestions to boost the use of chatbots. First, to enhance usefulness and user-friendliness, chatbot interfaces should be intuitive, responsive, and well-integrated with banking functions. Second, ensuring trust and perceived security is critical, which includes implementing robust security features and clearly communicating them to users. Third, to improve satisfaction, banks must focus on consistently meeting or exceeding user expectations through reliable and personalized chatbot experiences. Lastly, investments in digital literacy and support infrastructure (i.e., facilitating conditions) can further ease adoption, especially in emerging markets like India where adoption is still in its growth phase.

Theoretical Contributions

This study offers several important theoretical contributions to the growing body of literature on technology adoption, particularly in the context of AI-driven banking chatbots. First, the study unifies UTAUT and ECM into a single framework, capturing both pre- and post-adoption dynamics in chatbot use (e.g. perceived usefulness, ease of use, facilitating conditions) and affective responses (e.g. satisfaction, trust). This dual-theory approach addresses the limitations of prior research that often relied on single-theory models, offering a more holistic understanding of the adoption process. Second, it extends this framework with trust and perceived security, addressing critical yet underexplored constructs in fintech adoption theory. Third, by applying PLS-SEM mediation analysis and reporting VAF values, it clarifies how perceived usefulness, trust, and satisfaction channel users' perceptions into adoption intent, advancing mediation research. Lastly, the model has been tested in the Indian digital banking context, a rapidly evolving yet underexplored setting. By doing so, this study adds to the limited empirical evidence on chatbot adoption in emerging economies, offering theoretical insights that are globally relevant yet contextually grounded.

Practical Contributions

This study offers several meaningful practical contributions for banking institutions, chatbot developers, and digital transformation strategists. First, the study highlights that trust and satisfaction are essential mediators influencing adoption, urging banks to design chatbot experiences that are secure, transparent, and emotionally reassuring. Second, since perceived usefulness alone is not enough, developers must combine functional utility with user-friendly, responsive, and engaging interfaces to drive adoption. Third, the impact of facilitating conditions on trust and satisfaction emphasizes the need for strong user support systems, including help features, multilingual access, and fallback assistance. Fourth, the study guides decision-makers on which psychological factors to prioritize, helping them build more effective, user-centric chatbot strategies in digital banking. Together, these practical contributions can guide the development of more user-centric, secure, and trustworthy chatbot systems, leading to higher adoption and long-term customer engagement in the digital banking landscape.

Limitations and Future Research Directions

There are certain limits to the study despite the numerous scholarly and practical contributions reported. First, the study is limited to banking chatbot users in India, which may restrict the generalizability of the findings to other countries or cultural contexts. Future studies can replicate this model in different geographic or demographic settings to test for cross-cultural validity. Second, the research employed a cross-sectional survey design, capturing user perceptions at a single point in time. Longitudinal studies could provide deeper insights into how trust, satisfaction, and adoption intentions evolve over time. Third, the study focused on perceptual and self-reported data, which may be subject to biases such as social desirability or recall inaccuracy. Future research may integrate behavioral usage data or experimental designs for validation. Lastly, the model did not account for potential moderating variables such as age, digital literacy, or prior chatbot experience, which might influence the strength of relationships. Future research can apply multi-group analysis to uncover such variations.

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