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**Examining the Influence of Perceived AI Competencies on
Customer Satisfaction and Continuance Intention towards AI-
enabled Digital Banking Services in India**

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Abstract

AI-enabled digital banking is expanding; however, there remains limited understanding of how customers' perceptions of AI competencies influence satisfaction and continued usage. This study examined the relationships between Perceived AI Competencies (PAC), Customer Satisfaction (CS), and Continuance Intention (CI) among users of AI-enabled digital banking services in India. Convenience sampling was used in a quantitative, deductive, cross-sectional survey methodology. Using SPSS, descriptive statistics, reliability, correlation, and regression analysis were performed on data from 51 valid respondents. The findings demonstrated that while customer satisfaction had a large impact on continuing intention, PAC had a considerable and positive affect on both. H1, H2, and H3 were therefore supported. Further regression analysis revealed data that supported customer satisfaction's partly mediating function in the association between PAC and continuance intention. Overall, the study offers empirical data from sampled users in India and emphasises the significance of customers' perceptions of AI competency and happiness in promoting the ongoing use of digital banking services with AI capabilities.

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Chapter 1 Introduction

1.1 Background of the study

Industry 4.0 has intensified the integration of advanced digital technologies into contemporary business operations, reshaping how organisations create value and deliver their services. Within this technological shift, artificial intelligence (AI) has assumed an increasingly important role, enabling organisations to improve operational processes, utilise data more effectively for decision-making, and strengthen overall organisational performance. The banking sector has experienced particularly rapid AI adoption as financial institutions increasingly integrate intelligent technologies to revolutionise service delivery and respond to changing customer expectations for faster, more personalised and convenient banking services. Consequently, traditional service paradigms are being replaced by AI-enabled digital banking in banks, where AI is increasingly viewed as a strategic capability for strengthening competitiveness and sustaining long-term organisational performance (Sheth *et al.*, 2022; Lee, Tang and Jiang, 2023; Bhatnagr, Rajesh and Misra, 2024; Kumar and Manrai, 2024).

AI has become increasingly embedded within banking operations, changing both internal processes and the ways in which financial institutions interact with customers. Through machine learning, automated systems and analytical techniques, banks can process financial information more efficiently and support decisions that require timely and accurate information. Its applications now extend across activities such as automated customer assistance, identification of fraudulent transactions, evaluation of credit, and the delivery of financial recommendations tailored to customer needs. Collectively, these applications can strengthen the efficiency of banking processes while contributing to more responsive and secure service experiences. However, the growing use of AI does not necessarily remove the need for human expertise. Instead, its value can lie in complementing employees by providing technological support for quicker, better-informed and more customer-focused service decisions (Lee, Tang and Jiang, 2023; Sheth *et al.*, 2022; Bhatnagr, Rajesh and Misra, 2024; Hussain *et al.*, 2026).

AI-enabled digital banking refers to the incorporation of intelligent capabilities into digital banking channels to create more adaptive and customer-focused services. Technologies such as machine learning, natural language processing and predictive analytics allow banking systems to interpret customer information, tailor financial offerings and support decisions more efficiently. This distinguishes AI-enabled services from conventional digital banking, where technology primarily facilitates electronic transactions and access to banking functions. AI can also streamline repetitive activities and improve the consistency of service processes, while enabling banking interactions to respond more closely to individual customer requirements. Consequently, AI-enabled digital banking has become a strategic innovation that enables financial institutions to improve organisational performance while strengthening customer experience and maintaining competitiveness in an increasingly digital banking environment (Lee, Tang and Jiang, 2023; Bhatnagr, Rajesh and Misra, 2024; Hussain *et al.*, 2026).

India's fast digital revolution and growing financial technology ecosystem make it a strategically significant environment for studying AI-enabled digital banking. Government programs like Digital India, together with increasing smartphone penetration, internet accessibility and the widespread adoption of the **Unified Payments Interface (UPI)**, have accelerated the use of digital banking services and strengthened financial inclusion. These advancements have prompted banks to incorporate AI technologies into digital banking platforms in order to manage increasing transaction volumes and enhance service efficiency.

Consequently, India's rapid AI adoption, large digital banking customer base and evolving financial landscape provide an appropriate setting for investigating how AI competencies influence customer satisfaction and continuance intention towards AI-enabled digital banking services (Kumar and Manrai, 2024; Bhatnagr, Rajesh and Misra, 2024; Prasanth, 2025).

As AI-enabled digital banking continues to change, understanding customer perceptions and post-adoption behaviour has become progressively important for financial institutions. Customer satisfaction and continuance intention are acknowledged as important indicators of the sustained prosperity of banking services facilitated by AI. Banks must provide smart, customer-focused services that satisfy consumers' growing need for safe, customised, effective, and convenient digital banking experiences. When people believe AI-enabled banking services are dependable and efficient, customers are more likely to be content and keep using them. Thus, assessing client happiness and intention to continue is crucial for comprehending how AI competencies influence customers' continued engagement with AI-driven online banking platforms (Lee, Tang and Jiang, 2023; Zulaikha and Faricha, 2026; Hussain *et al.*, 2026).

Artificial intelligence is becoming more widely used in digital banking, which shows that long-term success cannot be guaranteed by technological innovation alone. Instead, financial institutions must understand how AI competencies influence customers' post-adoption behaviour, particularly their satisfaction and willingness. For banks, the value of AI implementation ultimately depends not only on technological investment but also on whether customers are willing to maintain their engagement with AI-supported services. As intelligent systems become more prominent within banking delivery, understanding customers' responses after adoption becomes increasingly important. Accordingly, this study examines how perceived AI competencies relate to Customer Satisfaction and continuance intention in the Indian digital banking setting. By focusing on these relationships, the research provides empirical insight into customers' post-adoption responses and contributes to understanding the role of perceived AI capability in an evolving digital banking environment (Bhatnagr, Rajesh and Misra, 2024; Kumar and Manrai, 2024; Hussain *et al.*, 2026).

1.2 Research Context

Financial institutions are now able to provide more intelligent, effective, and customer-focused services due to artificial intelligence's (AI) rapid usage, which has fundamentally altered digital banking. However, the successful operation of AI extends beyond technological investment, as long-term value depends on how customers perceive and continue using AI-enabled banking services. Consequently, for banks looking to improve customer relations and maintain competitiveness in a changing digital landscape, it is becoming more and more crucial to comprehend how AI competencies affect consumers' post-adoption behaviour. Within this context, the study explores how Perceived AI Competencies (PAC) are associated with Customer Satisfaction and Continuance Intention among users of AI-enabled digital banking services in India (Bhatnagr, Rajesh and Misra, 2024; Kumar and Manrai, 2024; Hussain et al., 2026).

India's banking landscape is becoming increasingly technology-driven as both public- and private-sector banks integrate AI into their service and operational systems. Major institutions such as the State Bank of India, HDFC Bank, ICICI Bank, Axis Bank and Kotak Mahindra Bank illustrate this transition through the use of virtual assistants, machine-learning applications and automated processes. Such technologies can support quicker responses to customer enquiries, simplify routine banking activities and enable services to be adapted more closely to individual customer requirements. Their growing presence indicates that AI is becoming embedded within the broader development of digital banking in India, as banks respond to customers' changing expectations while seeking improvements in the way services are delivered and managed (Sheth et al., 2022; Bhatnagr, Rajesh and Misra, 2024; Kumar and Manrai, 2024; Hussain et al., 2026).

India's wider digital development has created conditions that favour the expansion of AI-supported banking. Government-led initiatives such as Digital India have encouraged greater participation in electronic financial services, while the Unified Payments Interface (UPI) has made real-time digital transactions increasingly accessible. Alongside these developments, wider smartphone and internet availability and the rapid development of the FinTech sector have strengthened customers' access to digital financial channels. Together, these changes have contributed to an environment in which banks can extend AI-enabled services to a growing digital customer base while supporting broader developments in financial access and technological innovation (Kumar and Manrai, 2024; Bhatnagr, Rajesh and Misra, 2024; Sharma, 2026).

Even though AI-enabled digital banking is expanding quickly in India, a number of obstacles still stand in the way of its widespread adoption and sustained use. Customer acceptance remains uneven, particularly among users with a low level of digital literacy or a preference for traditional banking services. In addition, concerns regarding cybersecurity, online fraud and data privacy continue to influence customers' trust in AI-enabled banking platforms. Due to these difficulties, financial institutions must offer safe, dependable, and customised banking services that satisfy a wide range of customer demands. Therefore, understanding the factors that affect customer satisfaction and intention to continue are crucial to the long-term viability of AI-enabled digital banking in India (Sharma, 2026; Sharma and Singh, 2024; Hussain et al., 2026; Sheth et al., 2022).

1.3 Research Problem

Banks are committing considerable resources to digital innovation, with AI increasingly shaping the way services are delivered and customers are supported. Its use now covers areas such as automated assistance, personalised financial recommendations, fraud monitoring and technology-supported decision processes. Yet greater investment in these capabilities does not necessarily translate into higher Customer Satisfaction or sustained use of AI-enabled banking. This creates an important challenge for financial institutions: understanding which AI capabilities customers actually recognise as valuable and whether those perceptions encourage continued engagement with digital banking services. Addressing this issue is particularly relevant for banks seeking to generate lasting customer value from their investment in AI rather than viewing technological implementation itself as an indicator of success.

Research on AI in banking has developed across several areas, including technology adoption, chatbot use, trust, service quality, satisfaction and customer experience. Collectively, this work has helped explain how technological characteristics and customer-related factors shape engagement with AI-supported banking services (Othayoth and Khanna, 2024; Shah and Champaneri, 2024). Nevertheless, much of this literature examines particular AI applications or isolated dimensions of the customer experience rather than considering AI competency from a broader perspective. Consequently, less attention has been given to whether customers' perceptions of AI competencies are associated with their experiences after adoption, particularly their satisfaction and willingness to maintain their use of AI-enabled digital banking.

Despite the valuable contributions of previous studies, important gaps remain in the existing literature. Current research has primarily examined AI adoption, technology acceptance, customer trust, service quality and individual AI applications, with limited attention given to AI competencies as a comprehensive organisational capability. Instead of viewing AI as an integrated capability that affects customer outcomes, the majority of empirical research conceptualises AI through certain technology features or individual AI dimensions. In addition, there is slight empirical data to determine whether consumers' perceptions of AI skills increase customer happiness and, in turn, reinforce their intention to stick. Accordingly, limited empirical attention has been directed towards how perceived AI competencies relate simultaneously to Customer Satisfaction and continuance intention in AI-enabled digital banking, leaving this relationship open to further investigation (Santana and Díaz-Fernández, 2023; Lee and Zhou, 2025).

Established technology theories provide a useful basis for interpreting customer behaviour, although they may not fully capture the characteristics of AI-supported banking. TAM primarily considers acceptance in terms of users' perceptions of a technology's usefulness and ease of use, whereas ECM focuses on behaviour following adoption, particularly the role of confirmation and satisfaction in shaping continued usage (Davis, 1989; Bhattacharjee, 2001). Despite the fact that both theories are frequently used in research on digital banking, they mainly describe technology adoption and continuance behaviour rather than how consumers' perceptions of AI skills affect their happiness and continued usage of AI-enabled financial services. Therefore, using either theory independently provides only a partial explanation of customer behaviour.

However, although Indian studies have examined AI-enabled customer experience, digital literacy, trust, service quality and customer satisfaction, evidence remains limited regarding customers' perceptions of AI competencies as an integrated construct and their influence on satisfaction and continuance intention (Salman and Chaya, 2026; Kasinathan, Sampath and

Sampath, 2024). Moreover, findings from studies conducted in China, Indonesia and Pakistan may not be directly generalisable to India because digital infrastructure, customer behaviour, regulation and banking practices differ across national settings. Therefore, context-specific empirical investigation is required to explain how perceived AI competencies shape customer satisfaction and continued usage of AI-enabled digital banking services in India.

1.4 Research Aim

The study aims to assess how customers' perceptions of AI competencies relate to their satisfaction and willingness to continue using AI-enabled digital banking in India.

1.5 Research Objectives

1. To assess how customers evaluate the competencies demonstrated by AI within digital banking services.
2. To determine whether perceived AI competencies contribute to Customer Satisfaction with AI-enabled banking.
3. To evaluate the role of perceived AI competencies in shaping customers' intentions to maintain their use of AI-enabled banking.
4. To establish whether Customer Satisfaction is associated with customers' intentions to continue using these services.
5. To derive practical recommendations for banks on strengthening AI-enabled service capabilities to support satisfaction and sustained customer usage.

1.6 Research Question

Main Research Question

To what extent are perceived AI competencies associated with Customer Satisfaction and continuance intention among users of AI-enabled digital banking services in India?

Sub-questions

1. How do customers evaluate the competencies of AI used within digital banking?
2. To what extent are perceived AI competencies associated with customer satisfaction?
3. What role do perceived AI competencies play in customers' intentions to maintain their use of AI-enabled banking?
4. To what extent is Customer Satisfaction associated with continued usage intentions?
5. What practical improvements in AI-enabled banking could support greater Customer Satisfaction and sustained usage?

1.7 Significance of the study

The significance of this research lies in its focus on customers' perceptions of AI competency within digital banking, an area receiving less attention than established themes such as technology adoption, trust, service quality and individual AI applications (Shah and Champaneri, 2024; Othayoth and Khanna, 2024). Examining PAC alongside Customer Satisfaction and Continuance Intention provides an opportunity to consider AI-enabled banking beyond initial technology acceptance and towards customers' experiences after adoption. The use of TAM and ECM further provides a theoretical basis for connecting

technology perceptions with satisfaction and sustained usage behaviour (Santana and Díaz-Fernández, 2023; Ikhsan et al., 2025).

The study is also relevant to the ongoing development of AI-enabled banking in India. Understanding how customers respond to perceived AI capabilities may help financial institutions make more customer-focused decisions when developing digital services. The topic also has relevance for responsible AI implementation, particularly where transparency, privacy, security and customer protection are concerned (Shah and Champaneri, 2024; Shaikh et al., 2024).

1.8 Scope and Delimitations of the Study

This research is confined to users of AI-enabled retail banking services in India and considers three central constructs: Perceived AI Competencies (PAC), Customer Satisfaction and Continuance Intention. The investigation is undertaken from the customer perspective; therefore, bank employees, managers and other organisational stakeholders fall outside its boundaries. Likewise, conventional banking activities and financial technologies unrelated to AI-enabled digital banking are not examined. Empirical data were obtained through an anonymous structured questionnaire using a quantitative, cross-sectional design and convenience sampling. The research captures customer responses at one point in time and does not seek to compare individual banks or track behavioural changes over an extended period. These boundaries maintain a focused investigation that corresponds with the stated research aim and objectives.

1.9 Chapter Summary

This chapter established the foundation for investigating PAC, Customer Satisfaction and continuance intention within AI-enabled digital banking in India. It introduced the research context and problem, identified the gap motivating the investigation, and established the aim, objectives, research questions and hypotheses. The significance and boundaries of the research were also defined to clarify its intended focus. Together, these elements establish the direction for the empirical investigation undertaken in this study. Chapter 2 develops this foundation through a critical examination of relevant literature and the theoretical perspectives underpinning the proposed relationships among the study constructs.

Chapter 2 Literature Review

2.1 Introduction

This chapter develops the conceptual and empirical basis of the study through an evaluation of literature relevant to AI-enabled digital banking. Rather than considering previous studies individually, the review brings together and compares existing evidence to identify areas of agreement, disagreement and remaining gaps within the field. With this critical assessment, the chapter identifies established knowledge, highlights areas of agreement and disagreement among previous studies, examines methodological differences and identifies limitations that remain insufficiently addressed in the existing literature. As a result, the literature review offers a strong defence of the study by highlighting the need for more research on how AI competencies affect consumer satisfaction and intention to continue using AI-enabled digital banking services.

Evidence from previous studies is considered collectively to reveal where findings converge or differ and how variations in research methods have shaped the available evidence. The review then uses these insights to establish the unresolved research issue, construct the study's conceptual model and explain the theoretical reasoning behind the hypotheses tested in this research.

2.2 AI-enabled digital banking

Banking service delivery has progressively moved beyond branch-based and conventional digital channels towards systems in which AI plays a more active role. Its application is no longer restricted to automating routine activities; banks increasingly use AI-related capabilities to interpret customer information, respond to financial needs and support service development (Gallego-Gomez and De-Pablos-Heredero, 2020; Vousinas and Saluja, 2025). The extent to which these capabilities can be implemented successfully, however, differs across markets. Research in developing economies suggests that factors such as organisational readiness, supporting digital infrastructure, customer awareness and access to human assistance can shape the effectiveness of AI-supported banking services (Sheth et al., 2022). AI-enabled banking can therefore be understood as a combination of technological capability and organisational resources applied within the customer service environment, rather than merely as the digital automation of existing banking activities.

Customer responses to AI-supported banking appear to depend on a combination of functional and relational considerations. Research has linked evaluations of usefulness and ease of interaction, together with trust, security and personalised service, to how customers respond to these technologies both when adopting them and after they are in use (Sharma and Singh, 2024; Othayoth and Khanna, 2024; Hasan et al., 2026; Bhatnagr, Rajesh and Misra, 2024). However, rather than AI capabilities as an integrated organisational competence, the majority of research concentrates on single AI applications or technology-specific aspects. Consequently, the combined effects of cognitive, relational, and emotional AI competencies on consumer satisfaction and intention to continue are explained by scant empirical data. While recent research has broadened the definition of AI skills, it primarily focuses on organisational innovation or financial well-being rather than client outcomes in AI-enabled digital banking. (Lee and Zhou, 2025; Santana and Díaz-Fernández, 2023). Therefore, a clearer understanding of how integrated AI competencies shape customers' post-adoption behaviour remains necessary.

The majority of the literature agrees that AI-enabled digital banking has a lot to offer consumers and financial institutions. By automating repetitive operations, enhancing fraud detection, boosting predictive analytics, and providing tailored financial suggestions, AI technologies increase operational efficiency. (Ashrafuzzaman *et al.*, 2025; Hasan *et al.*, 2026). In addition, many customers continue to prefer human support for complex financial decisions, suggesting that AI enhances human knowledge rather than replaces it (Sheth *et al.*, 2022; Kumar and Manrai, 2024). These results show that the success of AI-enabled digital banking hinges on institutions' capacity to create clear, trustworthy and customer-centred AI systems, reinforcing the importance of examining AI competencies in the present study.

Even though the amount of research on AI-enabled digital banking is increasing, the methodological approaches used in previous studies are comparable. Most have adopted quantitative, cross-sectional survey designs with convenience sampling to examine technology adoption, customer trust, service quality and customer experience within single-country settings (Sharma and Singh, 2024; Othayoth and Khanna, 2024; Hasan *et al.*, 2026). While these studies offer insightful information, their methodological focus limits the wider applicability of the findings across different banking contexts and customer groups. Moreover, most research continues to examine individual AI applications or technology acceptance factors rather than AI competencies as an integrated organisational capability influencing post-adoption outcomes. While a small number of recent studies have explored AI competencies, empirical evidence remains limited, particularly in the Indian banking sector (Lee and Zhou, 2025; Santana and Díaz-Fernández, 2023). §

2.3 Artificial Intelligence Competencies

'Artificial Intelligence' (AI) competencies refer to organisational knowledge and go beyond the use of AI technologies. Capabilities and strategic routines required to create value from AI. Rather than viewing AI as a collection of algorithms or automated tools, recent literature conceptualises AI competencies as the capacity of a company to manage, integrate, and constantly enhance AI resources in accordance with strategic goals (Lee and Zhou, 2025; Santana and Díaz-Fernández, 2023). Sustainable competitive advantage depends more on an organisation's capacity to integrate, coordinate, and optimise AI throughout its operations than on AI adoption itself as these technologies become more widely available. Consequently, the literature has shifted from viewing AI as a technological resource to recognising AI competencies as a strategic capability that supports innovation, long-term value creation and customer-centred service delivery (Gallego-Gomez and De-Pablos-Heredero, 2020).

According to recent research, AI competences are a multifaceted notion that integrates organisational, human, and technological capabilities. Commonly identified dimensions include cognitive, analytical, relational, emotional and adaptive competencies. Cognitive and analytical competencies enable organisations to analyse data, produce insights, and facilitate well-informed decision-making, whereas relational and emotional abilities promote customer trust, foster human-AI collaboration, and enhance service interactions (Lee and Zhou, 2025). An organisation's ability to modify AI applications, procedures, and resources in response to evolving technology and shifting consumer demands is reflected in its adaptive competency. While scholars disagree on the relative significance of these factors, some prioritise technical and analytical skills, while others point to organisational culture and productive human-AI cooperation as the primary factors influencing AI performance. Nevertheless, the literature consistently suggests that technological capability alone is insufficient and that sustainable AI performance depends on the effective integration of technical, organisational and human capabilities (Santana and Díaz-Fernández, 2023; Gallego-Gomez

An increasing amount of empirical research shows that AI competencies positively influence both organisational performance and customer outcomes. Strong AI competencies enable banks to improve service quality, deliver personalised financial recommendations, enhance operational efficiency and create better customer experiences, leading to higher levels of customer contentment and loyalty (Hasan *et al.*, 2026; Othayoth and Khanna, 2024). Additionally, research indicates that dependable AI performance and productive customer interactions boost trust, which in turn motivates customers to stick with AI-enabled banking services (Sharma and Singh, 2024). Empirical results, however, are still conflicting. Some researchers argue that limited transparency, empathy and responsiveness in AI systems can reduce customer confidence, whereas others highlight the influence of cultural context and customer expectations on perceptions of AI-enabled services and their outcomes (Ni, 2024; Sheth *et al.*, 2022). These divergent results imply that the connection between customer outcomes and AI competencies is more complex than previously recognised and requires further empirical investigation.

Despite increasing interest in AI competencies, the available evidence is constrained in several respects. Much of the empirical work relies on cross-sectional survey data and non-probability samples, meaning that changes in perceptions over time remain largely unexplored. Studies have also operationalised AI competency in different ways, making comparison across findings difficult and leaving measurement relatively fragmented (Lee and Zhou, 2025; Santana and Díaz-Fernández, 2023). A further issue concerns context: existing evidence is largely drawn from settings outside India or approaches AI capability from an organisational rather than customer perspective. As a result, there is comparatively little evidence showing how customers' evaluations of AI capability are associated with satisfaction and intentions to maintain their use of AI-enabled banking in India. These unresolved issues establish the basis for the present investigation and provide a transition to the discussion of customer satisfaction.

2.4 Customer Satisfaction

Customer satisfaction reflects customers' overall evaluation of the experience they receive from a service provider and can shape whether that relationship is maintained over time. Its relevance is particularly pronounced in banking, where customers expect institutions handling their financial resources to provide interactions that are dependable, secure, accurate and responsive to their needs. As banking services become increasingly AI-enabled, customers also expect AI systems to deliver timely assistance, personalised recommendations and consistent service without errors or unnecessary complexity. Previous studies suggest that efficient service delivery, responsiveness, reliability and trust positively influence customer satisfaction, which subsequently motivates customers to keep utilising online banking services (Othayoth and Khanna, 2024; Sharma and Singh, 2024; Hasan *et al.*, 2026). Thus, a crucial post-adoption result for assessing the efficacy of AI-enabled banking services is customer happiness.

The benefits of AI for Customer Satisfaction are not consistent across the literature. Even where AI improves aspects of banking delivery, customers may respond negatively when they question how their data are handled, whether transactions remain secure, how automated decisions are reached, or whether system-generated recommendations can be relied upon. Human assistance may also remain preferable when financial issues are complex or personally sensitive (Ni, 2024; Sheth *et al.*, 2022). This indicates that satisfaction is shaped less by the mere availability of AI and more by the quality of the experience customers have when interacting with it.

Comparatively little attention has been given to whether AI competencies themselves contribute to customer satisfaction. In addition, existing evidence is largely based on cross-sectional studies conducted outside the Indian banking context, limiting understanding of how customers perceive AI competencies in one of the digital banking marketplaces with the quickest rate of growth on the globe. It is now more important than ever to identify the offerings that maximise customer pleasure. as Indian banks continue to increase their investment in AI technologies. This gap provides a clear justification for the present study and leads to the subsequent discussion of continuance intention.

2.5 Continuance Intention

Continuance intention concerns customers' inclination to maintain their engagement with a service once they have already experienced it. In AI-enabled digital banking, the concept therefore moves attention beyond initial acceptance towards customers' willingness to remain users of AI-supported services. This post-adoption perspective is important for banks because introducing an AI service does not itself ensure that customers will incorporate it into their ongoing banking activities. Sustained engagement is more likely to depend on whether customers continue to regard the service as worthwhile and dependable.

Customer satisfaction is frequently associated with this post-adoption decision, although evidence suggests that continued engagement may depend on the wider experience surrounding AI use. Customers may be more inclined to remain with AI-supported banking when interactions meet their expectations for usefulness, convenience and reliability. In contrast, doubts surrounding privacy and security, inaccurate automated responses, or insufficient access to human assistance can weaken customers' willingness to maintain that engagement (Ni, 2024; Sheth et al., 2022). Continuance intention should therefore be considered in relation to the overall experience customers develop with AI-enabled banking rather than technological performance in isolation.

2.6 Technology Acceptance Model (TAM)

Davis (1989) developed the Technology Acceptance Model (TAM) to understand individuals' responses to technology. Central to the model are perceived usefulness and perceived ease of use, which represent users' judgements about the benefits offered by a system and the effort involved in using it. Applied to digital banking, these concepts provide a basis for considering why customers may initially engage with technology when they believe it can make banking activities more useful and manageable. TAM is therefore relevant to the technological dimension of the present research (Davis, 1989).

Its explanatory value for this study is nevertheless limited. The principal concern of TAM is technology acceptance, whereas the present investigation considers what occurs after customers have already encountered AI-enabled banking. Customer Satisfaction and Continuance Intention, consequently, requires attention beyond the initial decision to adopt a technology. Furthermore, customers may judge AI-enabled services according to capabilities that extend beyond usefulness and ease of interaction. For this reason, TAM provides part of the theoretical foundation but is not used independently to explain the complete research model.

2.7 Expectation Confirmation Theory (ECM)

ECM shifts the theoretical emphasis from initial acceptance to customers' responses following technology use. Bhattacharjee (2001) proposes that users evaluate their experience against earlier expectations, with confirmation contributing to satisfaction and ultimately shaping the decision to maintain technology usage. This makes ECM particularly relevant to the present study because Customer Satisfaction and continuance intention represent post-adoption outcomes rather than initial acceptance. In the context of AI-enabled banking, the model helps explain why customers' evaluations after interacting with a service can matter for their willingness to remain users (Bhattacharjee, 2001).

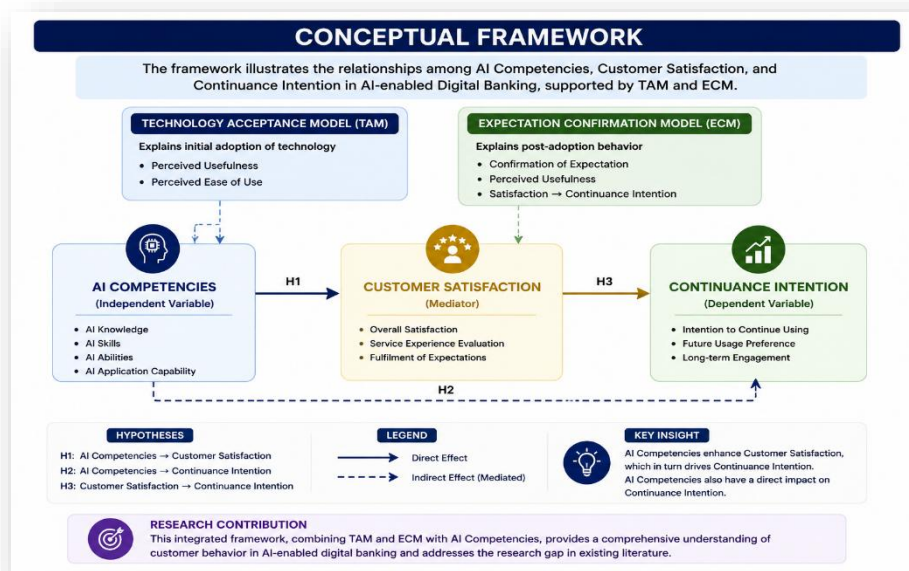
ECM does not, however, fully account for the distinctive capabilities of AI. Its emphasis on confirmation and satisfaction provides insight into continued usage but does not explicitly explain how customers evaluate the competency demonstrated by an AI system. Experiences with AI-supported banking may also involve considerations surrounding privacy, security, trust, service quality and the nature of automated interactions. Consequently, ECM is useful for explaining the post-adoption component of the research but does not independently capture PAC. Combining insights from TAM and ECM, therefore, enables the study to consider both customers' technology-related evaluations and their subsequent satisfaction and continuance intention.

2.8 Research Gap

Research into digital banking has generated substantial evidence on the factors associated with customers' technology-related decisions. Much of this work has centred on service quality, trust, satisfaction and technology acceptance, with established theoretical perspectives also being used to understand initial adoption and subsequent usage behaviour (Davis, 1989; Bhattacharjee, 2001). While this literature provides an important foundation, its emphasis has largely remained on conventional determinants of customer responses rather than on how customers evaluate the capabilities demonstrated by AI itself.

This leaves an important area insufficiently explored. PAC has received comparatively less attention as an antecedent of Customer Satisfaction and continuance intention within AI-enabled banking. Existing explanations of continued usage more commonly emphasise trust, service-related evaluations and satisfaction, while the specific role of customers' assessments of AI competency remains less developed. A further gap concerns theoretical coverage: TAM offers insight into technology-related evaluations, whereas ECM provides a post-adoption perspective, yet their complementary relevance to PAC, satisfaction and continued usage in AI-enabled banking remains underexplored. Evidence concerning these relationships among banking customers in India is also comparatively limited. Together, these gaps provide the basis for the conceptual model examined in this study.

2.9 Conceptual Framework



The conceptual framework developed for this study specifies the relationships among Perceived AI Competencies (PAC), Customer Satisfaction (CS) and Continuance Intention (CI). PAC is positioned as the independent variable, CS as the mediating variable and CI as the dependent variable. The model proposes that customers who evaluate the competencies of AI-enabled banking more favourably are likely to report greater satisfaction and stronger intentions to maintain their use of these services. It further proposes a direct relationship between PAC and CI, while CS provides a potential pathway through which PAC may relate to continued usage.

The framework draws on complementary insights from TAM and ECM. TAM provides a technology-orientated perspective for considering customers' evaluations of digital systems, whereas ECM contributes a post-adoption perspective in which satisfaction is relevant to subsequent usage intentions (Davis, 1989; Bhattacharjee, 2001). Neither perspective explicitly captures customers' assessment of AI competency; PAC is therefore incorporated to reflect this AI-specific dimension. Bringing these elements together enables the framework to examine whether perceptions of AI capability are associated with satisfaction and, subsequently, customers' willingness to remain engaged with AI-enabled digital banking.

2.10 Hypothesis Development

2.10.1 AI Competencies and Customer Satisfaction

The perceived capability of AI may also be relevant after customers have begun using AI-supported banking. Customers who experience AI as capable and useful within their banking activities may have greater reason to maintain their engagement with these services. This relationship connects the technology-orientated perspective of TAM with the post-adoption emphasis of ECM: the former informs customers' evaluations of technology, while the latter helps explain subsequent usage intentions. PAC is incorporated into this reasoning to capture customers' assessment of AI capability specifically. This leads to the second hypothesis:

H1: Perceived AI competencies are **positively associated with Customer Satisfaction** in AI-enabled digital banking.

2.10.2 AI Competencies and Continuance Intention

The perceived capability of AI may also be relevant after customers have begun using AI-supported banking. Customers who experience AI as capable and useful within their banking activities may have greater reason to maintain their engagement with these services. This relationship connects the technology-orientated perspective of TAM with the post-adoption emphasis of ECM: the former informs customers' evaluations of technology, while the latter helps explain subsequent usage intentions. PAC is incorporated into this reasoning to capture customers' assessment of AI capability specifically. This leads to the second hypothesis:

H2: Customers reporting stronger perceived AI competencies demonstrate **greater continuance intention** towards AI-enabled digital banking.

2.10.3 Customer Satisfaction and Continuance Intention

Satisfaction provides an important connection between customers' experience of a service and their subsequent behavioural intentions. Within ECM, experiences that meet or positively confirm users' expectations contribute to satisfaction, which can subsequently strengthen the intention to maintain technology use (Bhattacharjee, 2001). Applied to AI-enabled banking, customers who evaluate their experience more favourably may therefore be more inclined to remain engaged with the service. On this basis, the third hypothesis states:

H3: Greater Customer Satisfaction is **associated with stronger intentions to continue using AI-enabled digital banking services**.

2.11 Chapter Summary

This chapter established the literature and theoretical basis for examining PAC, Customer Satisfaction and continuance intention in AI-enabled digital banking. Comparison of previous research revealed areas that remain insufficiently addressed, providing the rationale for the relationships represented in the conceptual framework. Insights from TAM and ECM were used to support the theoretical reasoning underlying the study, from which three hypotheses were developed. Chapter 3 now explains the methodological approach used to collect and analyse the empirical evidence required to evaluate these relationships.

Chapter 3 Research Methodology

3.1 Introduction

This chapter explains how the empirical stage of the research was undertaken. The methodological choices were determined by the need to investigate the relationships among Perceived AI Competencies (PAC), Customer Satisfaction (CS) and Continuance Intention (CI) among users of AI-enabled digital banking services in India. Accordingly, the study was organised around the collection and statistical examination of quantitative evidence.

The discussion sets out the philosophical position and research approach before explaining the design and strategy used to obtain the data. It then details the study population, participant selection, questionnaire development and data collection process. The procedures used to prepare and analyse the responses in SPSS are also presented, together with the measures taken to address reliability, validity and research ethics. These methodological decisions provide the basis for evaluating the proposed relationships between the study constructs and answering the research objectives through empirical analysis.

3.2 Research Philosophy

The philosophical position adopted in research shapes what is regarded as acceptable knowledge and influences the way evidence is obtained and interpreted. It therefore has an important connection with decisions concerning research design, methods and analysis. Rather than selecting a philosophical stance independently of the investigation, it should be compatible with the nature of the research question and the form of evidence required to address it (Crotty, 1998; Saunders, Lewis and Thornhill, 2023).

Different positions are available within business and management research, including positivism, interpretivism, realism and pragmatism. These perspectives differ in their assumptions about reality, knowledge and how phenomena should be investigated. The appropriate position consequently depends on what the researcher intends to investigate and how evidence will be generated and evaluated (Bell, Bryman and Harley, 2022; Creswell and Creswell, 2023).

A positivist position was selected for the present research. The study investigates predefined relationships among PAC, CS and CI using numerical responses collected through a structured questionnaire and subsequently analysed statistically. This orientation is compatible with positivism because the investigation relies on observable and measurable evidence rather than participants detailed subjective interpretations. It also supports the testing of predetermined hypotheses through quantitative analysis while maintaining a consistent procedure across respondents (Saunders, Lewis and Thornhill, 2023; Creswell and Creswell, 2023).

3.3 Research Approach

The relationship between established theory and the evidence collected in a study can be approached through different forms of reasoning. Deduction moves from existing theoretical knowledge towards empirical testing, whereas induction develops theoretical understanding from patterns emerging within collected data (Saunders, Lewis and Thornhill, 2023; Bell, Bryman and Harley, 2022). The distinction is relevant here because this research does not seek to construct a new theory from participants' accounts; instead, relationships identified in advance are evaluated using quantitative evidence.

Deductive reasoning was therefore followed in this study. TAM and ECM, together with the literature reviewed in Chapter 2, informed the conceptual framework linking Perceived AI Competencies (PAC), Customer Satisfaction (CS) and Continuance Intention (CI). Three hypotheses were specified before the empirical analysis and subsequently assessed using data obtained from users of AI-enabled digital banking in India. This progression from theoretical foundations to predetermined hypotheses and statistical testing is consistent with a deductive approach (Creswell and Creswell, 2023; Saunders, Lewis and Thornhill, 2023).

3.4 Research Design

An explanatory design was used because the investigation centres on specified relationships among PAC, CS and CI rather than simply describing characteristics of digital banking users. The design allows the empirical evidence to be used to assess whether variation in one construct is statistically associated with variation in another. This directly reflects the study objectives and the hypotheses developed from the literature (Saunders, Lewis and Thornhill, 2023).

The investigation was quantitative and cross-sectional, with responses gathered at one point in time and analysed statistically. This design enabled the proposed relationships to be evaluated within the sampled users of AI-enabled digital banking in India. It should, however, be recognised that a cross-sectional design identifies statistical relationships within the observed data rather than establishing changes occurring over time.

3.5 Research Strategy

A survey strategy was used to obtain primary data directly from users of AI-enabled digital banking services in India. Participants completed a structured online questionnaire administered through Google Forms, allowing the same questions and response options to be presented consistently across the sample. This format also produced numerical responses suitable for subsequent statistical analysis in SPSS (Creswell and Creswell, 2023; Saunders, Lewis and Thornhill, 2023).

The survey strategy was compatible with the quantitative and deductive orientation of the research because the constructs and hypotheses had been established before data collection. It enabled information relating to PAC, CS and CI to be gathered in a standardised form and provided the empirical data required to evaluate the proposed relationships.

3.6 Research Population

The population was defined according to the characteristics required to address the research objectives. For this investigation, eligible participants were adults aged 18 years or above in India who had experience of AI-enabled digital banking. Defining these eligibility conditions ensured that responses were obtained from individuals able to evaluate the AI-related banking services considered in the research (Saunders, Lewis and Thornhill, 2023; Bell, Bryman and Harley, 2022).

Participants were required to be users of banking services incorporating AI-related features, which could include chatbots, virtual assistants, personalised financial recommendations or AI-supported fraud detection. Their direct exposure to such services enabled them to report their perceptions of AI competency, satisfaction and intention to maintain usage. The selected population was therefore consistent with the three constructs incorporated within the conceptual framework.

3.7 Sampling Technique

Participants were recruited through convenience sampling, which represents a non-probability approach to participant selection. This method was chosen in view of the practical time and resource boundaries of the research and enabled responses to be obtained from eligible AI-enabled digital banking users who were accessible to the researcher (Creswell and Creswell, 2023; Saunders, Lewis and Thornhill, 2023).

Following data collection and screening, 51 valid responses were retained for analysis in SPSS. Although this approach enabled the empirical stage of the study to be completed within the available constraints, convenience sampling does not provide every member of the target population with a known probability of selection. The resulting limitation concerning wider representation is therefore acknowledged when interpreting the findings.

3.8 Data Collection

Primary data were obtained directly from eligible participants because the investigation required information about customers' own perceptions and experiences of AI-enabled banking. A structured online questionnaire was administered through Google Forms, providing a consistent format for collecting responses relating to PAC, Customer Satisfaction and Continuance Intention. Direct collection was appropriate because these individual evaluations could not be adequately derived from secondary datasets or published material (Saunders, Lewis and Thornhill, 2023; Bell, Bryman and Harley, 2022).

Participation was voluntary, and respondents were informed about the purpose of the research before proceeding with the questionnaire. No personally identifying information was required for the analysis, and responses were handled anonymously and confidentially. Only the collected survey data relevant to the research objectives were subsequently prepared for statistical analysis.

3.9 Questionnaire Design

The research objectives, conceptual framework, and conclusions The construction of the questionnaires was based on information from the literature review. In order to gather background information about the respondents, the questionnaire included demographic questions. The questionnaire's general design was created to guarantee that the information gathered was pertinent to the study's goals. (Saunders, Lewis and Thornhill, 2023; Cohen, Manion and Morrison, 2018). A five-point Likert scale was used to measure the primary research constructs, and multiple-choice questions were used to gather demographic data. A scale from 1 (strongly disagree) to 5 (strongly agree) was used to gauge respondents' degree of agreement. Because it allows respondents to consistently express their ideas and produces data appropriate for statistical analysis using SPSS, the Likert scale is frequently used in quantitative research. (Bell, Bryman and Harley, 2022; Saunders, Lewis and Thornhill, 2023).

To make sure that responders could easily understand the questions, the questionnaire was constructed in simple, straightforward English. The questions were arranged rationally, starting with demographic and participant data questions and moving on to the primary study constructs. This framework was designed to make the questionnaire easier to complete while also improving the consistency and quality of the responses collected.

3.10 Data Analysis Technique

Following completion of the survey, the responses were transferred from Google Forms to Microsoft Excel for initial checking and preparation. The dataset was reviewed for completeness and accuracy before the valid responses were prepared for analysis. The resulting dataset was then analysed using SPSS. Screening the data before statistical testing helped ensure that the analysis was based on appropriately prepared responses (Pallant, 2020).

Several statistical procedures were undertaken to address the research objectives. Frequencies and percentages were used to describe respondent characteristics, while means and standard deviations summarised the study constructs. Cronbach's alpha was calculated to assess the internal consistency of the PAC, Customer Satisfaction and Continuance Intention measures. Pearson correlation coefficients were used to establish the direction and strength of associations among the constructs. Regression analysis was subsequently applied to evaluate the relationships represented by H1, H2 and H3 (Pallant, 2020; Field, 2018).

The statistical evidence was organised into tables and interpreted against the hypotheses and research objectives. An additional multiple regression analysis was also undertaken to explore the potential mediating role of Customer Satisfaction in the relationship between PAC and continuance intention.

3.11 Reliability, Validity and Ethical Considerations

Internal consistency was examined separately for the items measuring PAC, Customer Satisfaction and Continuance Intention. Cronbach's alpha was calculated in SPSS for each construct, with a coefficient of 0.70 or above used as the general benchmark for acceptable consistency (Tavakol and Dennick, 2011; Pallant, 2020). This assessment established whether the items grouped within each construct operated consistently enough for subsequent statistical analysis.

Validity was considered during the development of the research instrument by aligning questionnaire items with the conceptual framework, research objectives and relevant literature. Each group of items corresponded to one of the constructs investigated in the study, and the wording was kept clear to reduce possible misunderstanding by respondents. These considerations were used to support the relevance of the questionnaire content to the concepts being measured (Cohen, Manion and Morrison, 2018).

Ethical safeguards were incorporated into the data collection process. Before entering the survey, participants received information about the purpose of the research and were asked to provide consent. Participation was voluntary, and respondents could leave the survey rather than proceed. No personally identifying information was required for the analysis, and the collected responses were treated anonymously and confidentially. The data were retained for academic research purposes and handled in accordance with the ethical requirements of the study (Saunders, Lewis and Thornhill, 2023).

3.12 Chapter Summary

This chapter established the methodological basis of the empirical investigation. The research followed a positivist, deductive and quantitative orientation, using an explanatory cross-sectional survey design and convenience sampling. Primary data were obtained through a structured online questionnaire and analysed in SPSS using descriptive, reliability, correlation and regression procedures. The chapter also addressed the validity of the research instrument

and the ethical safeguards applied during data collection. Together, these methodological choices provided the basis for evaluating the proposed relationships among PAC, Customer Satisfaction and Continuance Intention. Chapter 4 reports the results generated from the empirical analysis.

Chapter 4: Data Analysis and Findings

4.1 Introduction

This chapter reports the empirical findings obtained from the survey data using SPSS. The analysis covers the characteristics of the respondents, descriptive statistics, reliability assessment, relationships among the study constructs, regression testing and the additional mediation analysis. The statistical evidence is used to evaluate the relationships specified in the research framework and the corresponding hypotheses.

4.2 Respondent Demographic Profile

Table 1: Demographic Profile of Respondents (N = 51)

Variable	Category	n	%
Gender	Female	22	43.1
	Male	28	54.9
	Prefer not to say	1	2.0

Age	18–25	14	27.5
	26–35	18	35.3
	36–45	11	21.6
	46–55	7	13.7
	56 years or above	1	2

Education	High School	3	5.9
	Diploma	6	11.8
	Bachelor's Degree	14	27.5
	Master's Degree	20	39.2
	Doctorate	6	11.8
	Other	2	3.9

Employment Status	Student	8	15.7
	Employed	22	43.1

	Self-Employed	14	27.5
	Unemployed	3	5.9
	Retired	2	3.9
	Other	2	3.9

Type of Bank	Public Sector Bank	13	25.5
	Private Sector Bank	28	54.9
	Foreign Bank	2	3.9
	Digital-Only Bank	5	9.8
	Other	3	5.9

AI-enabled banking use	Less than 1 year	18	35.3
	1–3 years	22	43.1
	3–5 years	6	11.8
	More than 5 years	5	9.8

There were 51 valid responses in all, and the analysis contained no missing demographic information. Although the proportion of male responders was slightly larger, the gender distribution was generally balanced. (54.9%) than female respondents (43.1%). The biggest age range was 26–35 years (35.3%), followed by 18–25 years (27.5%), indicating a greater concentration of younger adults within the sample. In terms of education, Master’s degree holders formed the largest group (39.2%), followed by Bachelor’s degree holders (27.5%), showing a relatively strong representation of higher educational qualifications. Employed respondents accounted for the largest employment group (43.1%), followed by self-employed respondents (27.5%). Private sector banks were the most commonly used (54.9%), compared with public sector banks (25.5%) and other banking categories. Regarding AI-enabled digital banking experience, 43.1% had used these services for 1–3 years, while 35.3% stated they had less than a year of experience, suggesting that most respondents had relatively recent experience with AI-enabled banking services.

4.3 Descriptive Statistics

Table 2: Descriptive Statistics of Study Variables

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Q9. The AI-enabled digital banking system performs banking tasks effectively.	51	1	5	3.88	1.243
Q10. The AI-enabled digital banking system provides accurate information	51	1	5	3.96	1.232
Q11. The AI-enabled digital banking system responds quickly to my requests.	51	1	5	4.18	1.144
Q12. The AI-enabled digital banking system understands my banking needs.	51	1	5	3.78	1.316
Q13. The AI-enabled digital banking system provides reliable services.	51	1	5	3.88	1.160
Q14. Overall, I consider the AI-enabled digital banking system to be competent.	51	1	5	3.92	1.214
Q15. Overall, I am satisfied with AI-enabled digital banking services.	51	1	5	3.69	1.304
Q16. AI-enabled digital banking services meet my expectations.	51	1	5	3.76	1.210
Q17. My experience with AI-enabled digital banking services has been satisfying	51	1	5	3.80	1.233
Q18. I am happy with the quality of AI-enabled digital banking services.	51	1	5	3.90	1.204
Q19. I intend to continue using AI-enabled digital banking services in the future.	51	1	5	4.12	1.070
Q20. I will frequently use AI-enabled digital banking services.	51	1	5	4.02	1.086
Q21. AI-enabled digital banking services will remain my preferred way of banking.	51	1	5	3.98	1.140
Q22. I would recommend AI-enabled digital banking services to others.	51	1	5	4.00	1.149
Valid N (listwise)	51				

Descriptive statistics were used to summarise responses for PAC, Customer Satisfaction (CS), and Continuance Intention (CI). All 51 respondents were included for each item, with responses ranging from 1 to 5 in accordance with the five-point Likert scale. For PAC (Q9–Q14), mean scores ranged from 3.78 to 4.18, with Q11/PAC3 recording the highest mean ($M = 4.18$, $SD = 1.144$), indicating the strongest agreement regarding the system's ability to respond quickly to requests. Customer Satisfaction (Q15–Q18) recorded mean scores between 3.69 and 3.90, with Q18/CS4 having the highest mean ($M = 3.90$, $SD = 1.204$), relating to satisfaction with service quality. For Continuance Intention (Q19–Q22), means ranged from 3.98 to 4.12, with Q19/CI1 demonstrating a comparatively strong commitment to keep utilising AI-enabled digital banking services, with the highest mean ($M = 4.12$, $SD = 1.070$). Overall, all mean scores were higher than the scale midpoint of 3, suggesting that responses to all three dimensions were largely positive.

4.4 Reliability Analysis

Table 3: Reliability Analysis of Study Constructs

Construct	Number of Items	Cronbach's Alpha (α)	Interpretation
Perceived AI Competencies (PAC)	6	0.875	Good
Customer Satisfaction (CS)	4	0.913	Excellent
Continuance Intention (CI)	4	0.926	Excellent

Reliability was assessed for PAC, CS and CI using Cronbach's alpha. All 51 respondents were included, with no cases excluded. PAC demonstrated good internal consistency ($\alpha = .875$), while CS showed excellent internal consistency ($\alpha = .913$). CI recorded the greatest dependability ($\alpha = .926$), further suggesting excellent internal consistency. All three values exceeded the commonly accepted threshold of .70, demonstrating sufficient reliability across the constructs. Therefore, all items were retained for subsequent analysis.

4.5 Correlation Analysis

Table 4. Correlation Analysis of Study Constructs

Correlations				
		PAC_Mean	CS_Mean	CI_Mean
PAC_Mean	Pearson Correlation	1	.828**	.790**
	Sig. (2-tailed)		<.001	<.001
	N	51	51	51
CS_Mean	Pearson Correlation	.828**	1	.831**
	Sig. (2-tailed)	<.001		<.001
	N	51	51	51
CI_Mean	Pearson Correlation	.790**	.831**	1
	Sig. (2-tailed)	<.001	<.001	
	N	51	51	51

** . Correlation is significant at the 0.01 level (2-tailed).

The correlation matrix showed positive associations across all three constructs. PAC was strongly correlated with CS ($r = .828$, $p < .001$) and CI ($r = .790$, $p < .001$). The largest

coefficient was observed between CS and CI ($r = .831$, $p < .001$). Each association reached statistical significance, showing that more favourable perceptions of AI competency and greater satisfaction were associated with stronger intentions to maintain the use of AI-enabled digital banking services.

4.6 Regression and Hypothesis Testing

Table 5. Regression Analysis and Hypothesis Testing

Hypothesis	Relationship	β	R^2	F	p	Decision
H1	PAC $\rightarrow$ CS	0.828	0.686	107.084	$< .001$	Supported
H2	PAC $\rightarrow$ CI	0.79	0.623	81.126	$< .001$	Supported
H3	CS $\rightarrow$ CI	0.831	0.69	109.105	$< .001$	Supported

The regression results provided support for all three hypothesised relationships. PAC accounted for 68.6% of the variation in CS ($\beta = .828$, $R^2 = .686$, $p < .001$), supporting H1. For H2, PAC explained 62.3% of the variance in CI, with the relationship remaining positive and statistically significant ($\beta = .790$, $R^2 = .623$, $p < .001$). The CS–CI model produced the largest explained variance, with CS accounting for 69.0% of the variation in CI ($\beta = .831$, $R^2 = .690$, $p < .001$); H3 was therefore supported. Diagnostic examination did not indicate a substantial problem requiring the removal of observations. One unusual residual was identified in the PAC–CS model, but its influence remained limited, with a maximum Cook’s distance of .180.

4.7 Mediation Analysis

Table 6 Multiple Regression Results for Continuance Intention

Predictor	B	SE	β	t	p
PAC	0.34	0.143	0.323	2.385	0.021
Customer Satisfaction	0.513	0.124	0.563	4.151	$< .001$

The additional regression model considered whether Customer Satisfaction (CS) could represent a potential pathway between PAC and Continuance Intention (CI). Together, PAC and CS accounted for 72.3% of the variance in CI ($R^2 = .723$; adjusted $R^2 = .711$), with the overall model reaching statistical significance, $F(2, 48) = 62.613$, $p < .001$. When both predictors were considered simultaneously, CS showed a positive and statistically significant association with CI ($\beta = .563$, $p < .001$). PAC also retained a statistically significant association with CI ($\beta = .323$, $p = .021$).

In comparison, the earlier regression model showed a substantially larger coefficient between PAC and CI ($\beta = .790$, $p < .001$). Following the inclusion of CS, this coefficient decreased to $\beta = .323$ but remained statistically significant. This pattern is consistent with partial mediation, indicating that CS may account for some of the association between PAC and CI while an

independent relationship between PAC and CI remains. As the indirect effect was not assessed through bootstrapping, this result is treated as indicative rather than conclusive evidence of mediation.

4.8 Chapter Summary

51 respondents' data were evaluated in this chapter, and PAC, CS, and CI all showed satisfactory dependability. Significant positive correlations between all three constructs were found by correlation analysis. The regression results, which showed that PAC strongly predicted both CS and CI while CS significantly predicted CI, supported H1, H2, and H3. Evidence supporting the partial mediating role of customer satisfaction was found in the supplementary mediation study. The results discussion in the following chapter is built upon these findings.

Chapter 5 Discussion, Conclusion and Recommendations

5.1 Introduction

This chapter interprets the empirical results in relation to the research objectives and the literature reviewed in Chapter 2. Particular attention is given to the relationships among Perceived AI Competencies (PAC), Customer Satisfaction (CS) and Continuance Intention (CI), including the additional analysis concerning the potential mediating role of CS. The chapter also considers the implications of the results, study limitations, directions for future research and the overall conclusions of the investigation.

5.2 Discussion of Key Findings

5.2.1 PAC and Customer Satisfaction (H1)

H1 was supported, with PAC showing a strong positive association with Customer Satisfaction ($\beta = .828$, $R^2 = .686$, $p < .001$). This pattern suggests that favourable customer evaluations of AI capability correspond with greater satisfaction when using AI-enabled banking. The result aligns with Hasan et al. (2026) and Othayoth and Khanna (2024), who associate effective AI-enabled services with improved customer outcomes, and with Sharma and Singh (2024), who emphasise the relevance of reliable AI performance and positive service interactions. This relationship nevertheless requires some qualification. Ni (2024) and Sheth et al. (2022) demonstrate that transparency, access to human interaction and customers' expectations can complicate their responses to AI. Viewed alongside these studies, the present result indicates that AI capability becomes meaningful for satisfaction through the way customers perceive and experience that capability, rather than through the presence of AI alone. The evidence therefore extends this discussion to the sampled users of AI-enabled digital banking in India.

5.2.2 PAC and Continuance Intention (H2)

Support was also obtained for H2, as PAC was positively associated with continuance intention ($\beta = .790$, $R^2 = .623$, $p < .001$). Customers who evaluated the capabilities of AI more favourably therefore tended to express stronger intentions to remain users of AI-enabled banking. This result corresponds with Sharma and Singh (2024), particularly their emphasis on reliable AI performance and effective interactions in sustaining customer engagement. However, the evidence reported by Ni (2024) and Sheth et al. (2022) provides an important counterpoint: concerns arising from AI interactions and the continued requirement for human assistance can affect customers' experiences. The present result therefore suggests that PAC is relevant to post-adoption behaviour, but continued engagement should not be attributed to technological capability in isolation.

TAM and ECM can also be used to interpret the results. While Bhattacharjee (2001) highlights pleasure and post-adoption appraisal in explaining continuance behaviour, Davis (1989) offers the theoretical foundation for comprehending consumers' acceptance of technology. These viewpoints are expanded by the current findings, which demonstrate that consumers' opinions of AI competency are strongly connected to their plan to keep utilising banking services powered by AI. This provides empirical evidence from the sampled Indian banking customers

that PAC may represent an important factor in understanding continued engagement with AI-enabled digital banking.

5.2.3 Customer Satisfaction and Continuance Intention (H3)

Customer satisfaction emerged as a particularly important predictor of continuance intention, with a significant positive effect ($\beta = .831$, $R^2 = .690$, $p < .001$), supporting H3. Of the three direct relationships tested, this was the strongest, suggesting that positive experiences with AI-enabled digital banking are closely associated with customers' willingness to maintain their usage. This result aligns with previous research showing that service reliability, responsiveness and positive banking experiences can strengthen satisfaction and encourage longer-term customer engagement (Othayoth and Khanna, 2024; Sharma and Singh, 2024; Hasan et al., 2026).

Additionally, this link aligns with the Expectation Confirmation Model (ECM). According to Bhattacharjee (2001), contentment is a key component of post-adoption behaviour, whereby positive assessments of a technology that has already been used influence the choice to keep using it. The current data supports this logic in AI-powered online banking. However, worries about security, privacy, and the limitations of AI interactions may potentially influence future use. (Ni, 2024; Sheth et al., 2022). Thus, sustaining satisfactory customer experiences appears important for encouraging longer-term engagement with AI-enabled banking among the respondents examined in this study.

5.2.4 Mediating Role of Customer Satisfaction

Further understanding of how Customer Satisfaction might function within the link between PAC and continuance intention is provided by the mixed regression model. An independent analysis of PAC revealed a significant favourable impact on continuing intention ($\beta = .790$, $p < .001$). After Customer Satisfaction was introduced into the model, the effect of PAC decreased substantially to $\beta = .323$ but remained significant ($p = .021$), while Customer Satisfaction independently predicted continuance intention ($\beta = .563$, $p < .001$). This pattern provides evidence consistent with partial mediation, suggesting that PAC may influence continued usage both directly and through customers' satisfaction with AI-enabled banking services.

This pattern is theoretically congruent with ECM, which centres post-adoption evaluation and ongoing technology use around pleasure (Bhattacharjee, 2001). Additionally, it expands on the literature that already exists, which shows that dependable and efficient AI-enabled services are linked to positive customer experiences and sustained engagement (Othayoth and Khanna, 2024; Sharma and Singh, 2024; Hasan et al., 2026). However, rather than being a conclusive proof of mediation, the evidence should be viewed cautiously because the indirect impact was not examined using bootstrapped confidence intervals.

5.3 Implications of the Findings

5.3.1 Academic Implications

Academically, the study provides empirical support for the relevance of PAC to both Customer Satisfaction and Continuance Intention. Its contribution lies in directing attention towards

customers' evaluations of AI competency, extending a literature that has more commonly emphasised trust, service quality, technology adoption and individual AI applications. The strong association observed between Customer Satisfaction and continuance intention also reinforces the relevance of ECM for understanding post-adoption behaviour in an AI-enabled banking setting. In this way, the research adds evidence from the sampled Indian banking users to the developing literature on customer responses to AI-supported financial services.

5.3.2 Practical Implications

Practically, banks should concentrate on both implementing AI technologies and making sure that clients view AI-enabled services as capable, dependable, and efficient. Enhancing the calibre of AI-powered services could lead to higher consumer satisfaction, which is particularly important given its strong relationship with Continuance Intention. Therefore, in order to promote ongoing use of AI-enabled banking services, banks should place a high priority on satisfying customer experiences. While creating and enhancing AI-enabled banking services, consideration should be given to privacy, security, transparency, and human support.

5.4 Limitations of the Study

Several features of the research design should be considered when interpreting the results. The sample consisted of 51 respondents, which restricts the extent to which the observed relationships can be generalised to the wider population of AI-enabled digital banking users in India. Participants were recruited through convenience sampling, creating the possibility that the sample may not adequately represent the broader target population. The cross-sectional design provides evidence from a single period and therefore does not capture whether PAC, Customer Satisfaction or continuance intention changes as customers gain further experience with AI-enabled banking. In addition, the analysis relies on self-reported questionnaire data and may therefore be affected by individual perceptions and response-related bias.

5.5 Recommendations for Future Research

Further research could address these limitations by examining a larger and more diverse population of AI-enabled banking users across India. The use of probability-based sampling could improve representation and reduce the potential bias associated with convenience sampling. A longitudinal design would also provide insight into whether PAC, Customer Satisfaction and continuance intention evolve as customers accumulate experience with AI-supported banking. Future models could additionally consider factors such as trust, privacy, security and transparency to determine whether they provide further explanation of customers' post-adoption responses.

5.6 Conclusion

The results highlight the importance of customers' perceptions of AI capability in shaping their experience of AI-enabled digital banking. Among the sampled users in India, stronger PAC was associated with greater Customer Satisfaction and continuance intention, providing support for H1 and H2. A positive association between satisfaction and CI also supported H3. Further analysis showed that the PAC–CI relationship weakened but remained significant when Customer Satisfaction was considered simultaneously. This pattern provides evidence consistent with partial mediation, suggesting that satisfaction may account for part of the connection between PAC and customers' intention to maintain usage. However, this

interpretation remains tentative because the indirect effect was not bootstrapped. Overall, the research demonstrates the relevance of both perceived AI capability and satisfaction to post-adoption intentions, while the findings should be interpreted within the limitations of the sample and research design.

6. References

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7. Appendix

7.1 Appendix A: Questionnaire

Section A: Consent

Q1. Do you voluntarily agree to participate in this research study?

- ☐ Yes
- ☐ No

If "No" → End Survey

Section B: Screening Question

Q2. Do you currently use AI-enabled digital banking services?

- ☐ Yes
- ☐ No

If "No" → End Survey

Section C: Demographic Information

Q3. Gender

- ☐ Male
- ☐ Female
- ☐ Prefer not to say

Q4. Age

- ☐ 18–25
- ☐ 26–35
- ☐ 36–45
- ☐ 46–55
- ☐ 56 years or above

Q5. Highest Educational Qualification

- ☐ High School
- ☐ Diploma
- ☐ Bachelor's Degree
- ☐ Master's Degree
- ☐ Doctorate
- ☐ Other

Q6. Employment Status

- ☐ Student
- ☐ Employed
- ☐ Self-employed
- ☐ Unemployed
- ☐ Retired
- ☐ Other

Q7. Which type of bank do you primarily use?

- ☐ Public Sector Bank
- ☐ Private Sector Bank
- ☐ Foreign Bank
- ☐ Digital-only Bank
- ☐ Other

Q8. How long have you been using AI-enabled digital banking services?

- ☐ Less than 1 year
- ☐ 1–3 years
- ☐ 3–5 years
- ☐ More than 5 years

Section D: Perceived AI Competencies, Customer Satisfaction, and Continuance Intention

Please indicate your level of agreement with each of the following statements, using the scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Perceived AI Competencies

Statement	1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
Q9. The AI-enabled digital banking system performs banking tasks effectively.	☐	☐	☐	☐	☐
Q10. The AI-enabled digital banking system provides accurate information.	☐	☐	☐	☐	☐
Q11. The AI-enabled digital banking system responds quickly to my requests.	☐	☐	☐	☐	☐
Q12. The AI-enabled digital banking system understands my banking needs.	☐	☐	☐	☐	☐
Q13. The AI-enabled digital banking system provides reliable services.	☐	☐	☐	☐	☐
Q14. Overall, I consider the AI-enabled digital banking system to be competent.	☐	☐	☐	☐	☐

Customer Satisfaction

Statement	1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
Q15. Overall, I am satisfied with AI-enabled digital banking services.	☐	☐	☐	☐	☐
Q16. AI-enabled digital banking services meet my expectations.	☐	☐	☐	☐	☐
Q17. My experience with AI-enabled digital banking services has been satisfying.	☐	☐	☐	☐	☐
Q18. I am happy with the quality of AI-enabled digital banking services.	☐	☐	☐	☐	☐

Continuance Intention

Statement	1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
Q19. I intend to continue using AI-enabled digital banking services in the future.	☐	☐	☐	☐	☐
Q20. I will frequently use AI-enabled digital banking services.	☐	☐	☐	☐	☐
Q21. AI-enabled digital banking services will remain my preferred way of banking.	☐	☐	☐	☐	☐
Q22. I would recommend AI-enabled digital banking services to others.	☐	☐	☐	☐	☐

7.2 Appendix B: SPSS Output

7.2.1 Frequencies

		Statistics					
		Gender	Age	Highest Educational Qualification	Employment Status	Type of Bank	Duration of AI-enabled digital banking use
N	Valid	51	51	51	51	51	51
	Missing	0	0	0	0	0	0

Frequency Table

		Gender			
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	22	43.1	43.1	43.1
	Male	28	54.9	54.9	98.0
	Prefer not to say	1	2.0	2.0	100.0
	Total	51	100.0	100.0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-25	14	27.5	27.5	27.5
	26-35	18	35.3	35.3	62.7
	36-45	11	21.6	21.6	84.3
	46-55	7	13.7	13.7	98.0
	56 years or above	1	2.0	2.0	100.0
	Total	51	100.0	100.0	

HighestEducationalQualification

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High School	3	5.9	5.9	5.9
	Diploma	6	11.8	11.8	17.6
	Bachelor's Degree	14	27.5	27.5	45.1
	Master's Degree	20	39.2	39.2	84.3
	Doctorate	6	11.8	11.8	96.1
	Other	2	3.9	3.9	100.0
	Total	51	100.0	100.0	

Employment Status

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Student	8	15.7	15.7	15.7
	Employed	22	43.1	43.1	58.8
	Self-Employed	14	27.5	27.5	86.3
	Unemployed	3	5.9	5.9	92.2
	Retired	2	3.9	3.9	96.1
	Other	2	3.9	3.9	100.0
	Total	51	100.0	100.0	

Type of Bank

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Public Sector Bank	13	25.5	25.5	25.5
	Private Sector Bank	28	54.9	54.9	80.4
	Foreign Bank	2	3.9	3.9	84.3
	Digital-only Bank	5	9.8	9.8	94.1
	Other	3	5.9	5.9	100.0
	Total	51	100.0	100.0	

Duration of AI-enabled digital banking use

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 1 year	18	35.3	35.3	35.3
	1-3 years	22	43.1	43.1	78.4
	3-5 years	6	11.8	11.8	90.2
	More than 5 years	5	9.8	9.8	100.0
	Total	51	100.0	100.0	

7.2.2 Reliability of Perceived AI Competencies

Case Processing Summary

		N	%
Cases	Valid	51	100.0
	Excluded ^a	0	.0
	Total	51	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.875	6

Item Statistics

	Mean	Std. Deviation	N
Q9. The AI-enabled digital banking system performs banking tasks effectively.	3.88	1.243	51
Q10. The AI-enabled digital banking system provides accurate information	3.96	1.232	51
Q11. The AI-enabled digital banking system responds quickly to my requests.	4.18	1.144	51
Q12. The AI-enabled digital banking system understands my banking needs.	3.78	1.316	51
Q13. The AI-enabled digital banking system provides reliable services.	3.88	1.160	51
Q14. Overall, I consider the AI-enabled digital banking system to be competent.	3.92	1.214	51

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q9. The AI-enabled digital banking system performs banking tasks effectively.	19.73	22.563	.746	.841
Q10. The AI-enabled digital banking system provides accurate information	19.65	22.233	.789	.834
Q11. The AI-enabled digital banking system responds quickly to my requests.	19.43	25.970	.484	.883
Q12. The AI-enabled digital banking system understands my banking needs.	19.82	22.348	.711	.848
Q13. The AI-enabled digital banking system provides reliable services.	19.73	23.683	.699	.850
Q14. Overall, I consider the AI-enabled digital banking system to be competent.	19.69	23.820	.644	.859

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
23.61	32.923	5.738	6

7.2.3 Reliability of Customer Satisfaction

Case Processing Summary

		N	%
Cases	Valid	51	100.0
	Excluded ^a	0	.0
	Total	51	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.913	4

Item Statistics

	Mean	Std. Deviation	N
Q15. Overall, I am satisfied with AI-enabled digital banking services.	3.69	1.304	51
Q16. AI-enabled digital banking services meet my expectations.	3.76	1.210	51
Q17. My experience with AI-enabled digital banking services has been satisfying	3.80	1.233	51
Q18. I am happy with the quality of AI-enabled digital banking services.	3.90	1.204	51

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q15. Overall, I am satisfied with AI-enabled digital banking services.	11.47	11.134	.761	.903
Q16. AI-enabled digital banking services meet my expectations.	11.39	11.323	.819	.881
Q17. My experience with AI-enabled digital banking services has been satisfying	11.35	10.993	.849	.871
Q18. I am happy with the quality of AI-enabled digital banking services.	11.25	11.594	.782	.894

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
15.16	19.455	4.411	4

7.2.4 Reliability of Continuance Intention

Case Processing Summary

	N	%
Cases		
Valid	51	100.0
Excluded ^a	0	.0
Total	51	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.926	4

Item Statistics

	Mean	Std. Deviation	N
Q19. I intend to continue using AI-enabled digital banking services in the future.	4.12	1.070	51
Q20. I will frequently use AI-enabled digital banking services.	4.02	1.086	51
Q21. AI-enabled digital banking services will remain my preferred way of banking.	3.98	1.140	51
Q22. I would recommend AI-enabled digital banking services to others.	4.00	1.149	51

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q19. I intend to continue using AI-enabled digital banking services in the future.	12.00	9.560	.828	.904
Q20. I will frequently use AI-enabled digital banking services.	12.10	9.570	.809	.910
Q21. AI-enabled digital banking services will remain my preferred way of banking.	12.14	9.001	.860	.892
Q22. I would recommend AI-enabled digital banking services to others.	12.12	9.186	.816	.908

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
16.12	16.186	4.023	4

7.2.5 Regression of PAC and CS

Descriptive Statistics

	Mean	Std. Deviation	N
CS_Mean	3.7892	1.10269	51
PAC_Mean	3.9346	.95631	51

Correlations

		CS_Mean	PAC_Mean
Pearson Correlation	CS_Mean	1.000	.828
	PAC_Mean	.828	1.000
Sig. (1-tailed)	CS_Mean	.	<.001
	PAC_Mean	.000	.
N	CS_Mean	51	51
	PAC_Mean	51	51

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	PAC_Mean ^b	.	Enter

a. Dependent Variable: CS_Mean

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.828 ^a	.686	.680	.62411	1.443

a. Predictors: (Constant), PAC_Mean

b. Dependent Variable: CS_Mean

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	41.710	1	41.710	107.084	<.001 ^b
	Residual	19.086	49	.390		
	Total	60.797	50			

a. Dependent Variable: CS_Mean

b. Predictors: (Constant), PAC_Mean

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients		Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta	t		Lower Bound	Upper Bound
1	(Constant)	.031	.374		.084	.933	-.719	.782
	PAC_Mean	.955	.092	.828	10.348	<.001	.770	1.141

a. Dependent Variable: CS_Mean

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.9864	4.8067	3.7892	.91335	51
Residual	-2.37410	1.37590	.00000	.61784	51
Std. Predicted Value	-3.069	1.114	.000	1.000	51
Std. Residual	-3.804	2.205	.000	.990	51

a. Dependent Variable: CS_Mean

7.2.6 Regression of PAC and CI

Descriptive Statistics

	Mean	Std. Deviation	N
CI_Mean	4.0294	1.00579	51
PAC_Mean	3.9346	.95631	51

Correlations

		CI_Mean	PAC_Mean
Pearson Correlation	CI_Mean	1.000	.790
	PAC_Mean	.790	1.000
Sig. (1-tailed)	CI_Mean	.	<.001
	PAC_Mean	.000	.
N	CI_Mean	51	51
	PAC_Mean	51	51

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	PAC_Mean ^b	.	Enter

a. Dependent Variable: CI_Mean

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.790 ^a	.623	.616	.62346	2.149

a. Predictors: (Constant), PAC_Mean

b. Dependent Variable: CI_Mean

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.534	1	31.534	81.126	<.001 ^b
	Residual	19.047	49	.389		
	Total	50.581	50			

a. Dependent Variable: CI_Mean

b. Predictors: (Constant), PAC_Mean

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.762	.373		2.042	.047	.012	1.512
	PAC_Mean	.830	.092	.790	9.007	<.001	.645	1.016

a. Dependent Variable: CI_Mean

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.5924	4.9141	4.0294	.79416	51
Residual	-1.86050	1.60834	.00000	.61720	51
Std. Predicted Value	-3.069	1.114	.000	1.000	51
Std. Residual	-2.984	2.580	.000	.990	51

a. Dependent Variable: CI_Mean

7.2.7 Regression of CI and CS

Descriptive Statistics

	Mean	Std. Deviation	N
CI_Mean	4.0294	1.00579	51
CS_Mean	3.7892	1.10269	51

Correlations

		CI_Mean	CS_Mean
Pearson Correlation	CI_Mean	1.000	.831
	CS_Mean	.831	1.000
Sig. (1-tailed)	CI_Mean	.	<.001
	CS_Mean	.000	.
N	CI_Mean	51	51
	CS_Mean	51	51

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	CS_Mean ^b	.	Enter

a. Dependent Variable: CI_Mean

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.831 ^a	.690	.684	.56561	2.308

a. Predictors: (Constant), CS_Mean

b. Dependent Variable: CI_Mean

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34.905	1	34.905	109.105	<.001 ^b
	Residual	15.676	49	.320		
	Total	50.581	50			

a. Dependent Variable: CI_Mean

b. Predictors: (Constant), CS_Mean

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.158	.286		4.049	<.001	.583	1.733
	CS_Mean	.758	.073	.831	10.445	<.001	.612	.903

a. Dependent Variable: CI_Mean

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.9160	4.9468	4.0294	.83552	51
Residual	-1.49970	1.75801	.00000	.55993	51
Std. Predicted Value	-2.529	1.098	.000	1.000	51
Std. Residual	-2.651	3.108	.000	.990	51

a. Dependent Variable: CI_Mean

7.2.8 Regression of mediation

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	CS_Mean, PAC_Mean ^b	.	Enter

a. Dependent Variable: CI_Mean

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.850 ^a	.723	.711	.54037

a. Predictors: (Constant), CS_Mean, PAC_Mean

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	36.565	2	18.283	62.613	<.001 ^b
	Residual	14.016	48	.292		
	Total	50.581	50			

a. Dependent Variable: CI_Mean

b. Predictors: (Constant), CS_Mean, PAC_Mean

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error				Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.746	.323		2.306	.025	.096	1.396		
	PAC_Mean	.340	.143	.323	2.385	.021	.053	.627	.314	3.185
	CS_Mean	.513	.124	.563	4.151	<.001	.265	.762	.314	3.185

a. Dependent Variable: CI_Mean

Collinearity Diagnostics^a

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	PAC_Mean	CS_Mean
1	1	2.947	1.000	.01	.00	.00
	2	.042	8.383	.83	.02	.17
	3	.011	16.629	.16	.97	.82

a. Dependent Variable: CI_Mean