Designing Trust: A Correlational Study of UI Design Elements and AI Tool Features on Consumer Engagement in AI -Powered Banking Apps

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Abstract

The rapid evolution of artificial intelligence (AI) has catalysed a transformative shift in the global banking landscape, with consumers increasingly turning to AI -powered applications for everyday financial management (Chukwudi et al., 2023). In response, fintech companies are intensifying efforts to enhance user experience through a seamless integration of intelligent functionalities and intuitive design. The intersection of user interface (UI) design and AI -driven personalisation has emerged as a critical determinant of user trust, satisfaction, and sustained engagement (Md Ashrafuzzaman *et al, 2025)*. This study investigates the relationship between user interface design elements, such as color palette, information density, and gamification, and AI -driven banking features, including savings recommendations, fraud alerts, and spending categorisation (Independent variable), to understand their combined impact on consumer engagement (dependent variable) in AI -powered financial platforms.

Employing a mixed-methods design, the study combines quantitative user surveys with qualitative insights to assess engagement metrics (including session frequency, feature adoption, and duration of use) alongside perceptions of UI aesthetics and AI functionality. Statistical analyses, including correlation and regression modeling, will identify significant predictors of engagement. Meanwhile, open-ended responses will enrich the understanding of user trust, perceived value, and satisfaction. In conclusion, the results demonstrate that while UI design establishes the conditions for trust and ease of use, AI features provide sustained, functional value that drives consistent engagement. These findings highlight the importance of a dual-focus development strategy in fintech, one that equally prioritises intuitive, high-quality interface design and impactful, value-driven AI capabilities to cultivate strong and enduring consumer relationships.

In conclusion, the results demonstrate that while UI design establishes the conditions for trust and ease of use, AI features provide sustained, functional value that drives consistent engagement. These findings highlight the importance of a dual-focus development strategy in fintech, one that equally prioritises intuitive, high-quality interface design and impactful, value-driven AI capabilities to cultivate strong and enduring consumer relationships.

Keywords: AI-powered banking, UI design, consumer engagement, trust, gamification, personalisation, fintech, human-AI interaction

Chapter 1: Introduction

The rapid evolution of artificial intelligence (AI) has revolutionized the financial sector, with AI-powered banking applications becoming a cornerstone of modern financial management (Chukwudi et al., 2023)). As fintech companies strive to enhance user experience, the interplay between user interface (UI) design and AI-driven functionalities has emerged as a critical factor influencing consumer trust, satisfaction, and engagement (Chitrakar et al., 2024). Despite the growing adoption of AI in banking, there remains a gap in understanding how specific UI design elements such as color schemes, information density, and gamification interact with AI features like savings recommendations, fraud alerts, and spending categorization to shape user engagement (Indriasari et al., 2022).

In this evolving digital landscape, the interplay between effective user interface design and AI-driven personalisation has emerged as a pivotal factor influencing user trust, overall satisfaction, and, crucially, sustained consumer engagement with banking applications (Paneru et al., 2024 ; Kumarasinghe, 2024). A well-designed user experience (UX) is no longer merely a competitive advantage but a fundamental requirement for digital banking products to succeed and retain users in a crowded market (Kreger, 2023). Poor design, conversely, can lead to frustration, disengagement, and a potential loss of customers (Kreger, 2023).

Although there is an increasing amount of research focused on AI in finance and UI/UX design, a thorough comprehension of the interplay between specific UI design components and AI-driven banking functionalities in shaping consumer engagement still presents opportunities for deeper investigation. At the same time research has explored how UI aesthetics impact consumer motivation (Cheng, 2025) and how AI features affect user satisfaction and continuation intention (Puneett Bhatnagr and Rajesh, 2024), the empirical literature consistently also demonstrates that when security features are effectively communicated through UI design and reinforced by reliable system performance, users exhibit higher trust levels and greater engagement willingness.

Thus , it is necessary to examine the joint effect of these separate but related elements. Moreover, the essential importance of user trust in AI-driven systems, especially in the sensitive area of financial services, requires further examination (Bach et al., 2022; Hari et al., 2021).

This study seeks to bridge this gap by examining the relationship between UI design and AI functionalities (independent variables) and their collective impact on consumer engagement (dependent variable) in AI-powered banking apps and their independent impact on building trust and maintaining consumer engagement. Engagement will be measured through session frequency, feature adoption rates, and duration of use, alongside qualitative insights into user perceptions of trust and usability (Ayomiposi Feyisekemi Akinwale 2022; Runsewe *et al.*, 2024).

Utilising a mixed-methods research approach, this study will combine quantitative user surveys to collect measurable information on engagement metrics and views regarding UI aesthetics and AI performance. This will be enhanced by qualitative insights gathered from open-ended answers, broadening the comprehension of user experiences, trust, and perceived value. Statistical methods, such as correlation and regression analysis, will be employed to determine important predictors of engagement, offering empirical support for the examined relationships.

The findings will provide actionable insights for fintech developers, enabling the creation of more intuitive, engaging, and trustworthy financial platforms. By integrating perspectives from design psychology, AI usability, and consumer behavior, this research contributes to the broader discourse on human-AI interaction in fintech, offering strategies to improve digital retention and long-term user relationships (Rohit et al., 2025).

Chapter 2: Literature Review

This chapter offers a critical synthesis of the literature relevant to understanding the relationship between User Interface (UI) design, Artificial Intelligence (AI) features, and consumer engagement within digital banking applications. The central aim is to build a solid theoretical and empirical foundation for the study by engaging with scholarship from information systems, design psychology, human-computer interaction (HCI), and financial technology. The review is organised thematically, beginning with an exploration of the historical and strategic development of digital banking to provide essential context. It then examines the key constructs of AI integration, UI design, and consumer engagement by considering their theoretical grounding and empirical support. Finally, the chapter draws these strands together to identify the research gap: the lack of integrated analysis on how specific UI components and AI-driven features collectively influence user trust and engagement. This progression, from broad contextual framing to focused theoretical discussion, leads to a clear justification for the research undertaken in this dissertation.

2.1 The Evolution of Digital Banking: From Automation to AI-Personalisation

The development of digital banking has been shaped by successive waves of technological innovation, evolving from basic electronic services to the sophisticated, artificial intelligence-enabled platforms used today. Its origins can be traced to the mid-1970s with the introduction of Automated Teller Machines (ATMs), which provided consumers with unprecedented access to their finances (Teplov, Danii, 2019). This milestone laid the groundwork for more complex digital solutions, followed in the late 1990s by the introduction of SMS banking and the rapid expansion of internet banking services. Early adopters such as Stanford Federal Credit Union (1994) and Wells Fargo (1996) were instrumental in popularising online banking, expanding consumer access and paving the way for mainstream adoption. The exponential rise in personal computer and smartphone usage during the twenty-first century accelerated this trajectory, transforming consumer behaviour to the extent that mobile devices are now the primary channel for managing financial activities (Cheng, 2025). As a result, digital banking has grown to encompass a wide spectrum of services, ranging from interbank transfers and global fund movements to bill payments, account management tools, and virtual safe deposit services (Ayomiposi Feyisekemi Akinwale, 2022), reflecting both rapid technological progress and evolving consumer expectations.

The current stage of banking innovation, often described as "Digital Bank 4.0," is defined by the integration of advanced technologies such as artificial intelligence, distributed ledger systems, cloud computing, and predictive data analytics (Indriasari et al., 2022). This transformation has spurred the emergence of digital-first challenger banks such as Monzo, N26, Revolut, and Wise, alongside the rapid growth of fintech companies operating through mobile-first platforms (Ayomiposi Feyisekemi Akinwale, 2022). These institutions are redefining consumer expectations by prioritising flexibility, accessibility, and enhanced security, while delivering greater operational efficiency. A key focus of this phase is the development of more intelligent and responsive banking ecosystems, where real-time data analytics embedded within user interfaces enable adaptive and personalised interactions. For example, platforms can dynamically adjust content during customer use, not only facilitating transactions but also offering customised product recommendations and retention strategies (Indriasari et al., 2022; Md Ashrafuzzaman et al., 2025). Such practices align with the Resource-Based View (RBV) of strategic management, in which the effective deployment of technological assets such as AI and analytics serves as a distinctive capability that underpins competitive advantage (Barney, 1991).

Alongside these advancements, the digital banking sector has increasingly embraced customer orientation as a strategic priority, requiring a shift toward behaviour-informed service design. Financial institutions now rely heavily on analysing user interactions to generate insights into consumer preferences, needs, and behavioural patterns (Kartikey Koti, 2024). These insights inform the design of customised financial products, optimised service pathways, and targeted marketing strategies tailored to individual users. This process involves the application of large-scale data analysis, AI-driven personalisation, and adaptive interface design to automate decision-making, streamline service delivery, and reinforce customer relationships (Lin, 2025). In this sense, digital banking no longer represents merely the online delivery of financial services but a fundamental reconfiguration of the banking experience, shaped by continuous data collection, customer profiling, and adaptive frameworks (Liu et al., 2024). Nevertheless, challenges remain: usability issues such as complex navigation, delayed system responses, and technical failures continue to limit user experience in some platforms, as evidenced by studies of applications like “B App” in Sri Lanka (Kumarasinghe, 2024). These findings highlight that while technology continues to advance, ensuring a seamless and secure user experience remains central to the success of digital banking.

2.2 Integration of AI and UI design into Online Banking to influence Consumer Engagement

The integration of Artificial Intelligence (AI) into online banking must first be understood within the broader context of digital transformation in financial services. The literature identifies six interconnected macro-level drivers reshaping the banking industry: technological innovation, ecosystem-based business models, sustainability imperatives, digital asset proliferation, evolving workforce dynamics, and shifting regulatory environments (Felipe et al., 2025). These trends highlight that AI adoption is not a standalone phenomenon but part of a systemic restructuring of banking practices that extends across retail, corporate, and capital market functions. Within this environment, Generative AI has emerged as a particularly influential enabler, capable of automating complex processes, generating tailored insights, and supporting intelligent service delivery (Jai, 2024; Generative AI for Enhanced UI Design, 2023). The relevance of this literature lies in demonstrating that AI-enabled systems align with rising consumer expectations for speed, convenience, and seamless integration, positioning AI as central to the creation of more adaptive, customer-centric banking ecosystems. This broader perspective provides the foundation for understanding why AI is an essential lens for studying consumer engagement in digital banking.

A second stream of literature focuses on the core domains of AI application in banking, namely customer service, security, and personalisation. Customer-facing AI systems, most notably intelligent chatbots, have evolved from rule-based scripts into sophisticated assistants capable of handling complex queries and delivering personalised guidance (Hari et al., 2021; Rohit et al., 2025). This shift reflects the sector's movement towards automated service models designed to balance efficiency with user satisfaction. Security-focused research emphasises AI's role in fraud detection, anomaly recognition, and biometric verification (Layla Abdel-Rahman Aziz & Andriansyah, 2023; Olowu et al., 2024), where machine learning techniques and neural networks enable real-time risk assessment. Personalisation, meanwhile, represents one of AI's most transformative contributions, with systems generating tailored financial recommendations and adaptive interface experiences (Md Ashrafuzzaman et al., 2025; Chukwudi et al., 2023). The relevance of this body of work lies in showing how AI is not only optimising operations but also reshaping the way consumers interact with financial platforms—an essential consideration for examining engagement. However, the literature also raises critical challenges: adoption depends on consumer perceptions of usefulness, transparency, and trust, factors often underestimated in technically focused studies.

Parallel to AI-focused scholarship, another body of literature examines user interface (UI) design as a determinant of consumer trust and engagement in digital banking. Drawing from design psychology, human-computer interaction, and institutional theory, this research emphasises that user-centric design goes beyond aesthetics to affect decision-making efficiency, trust formation, and platform credibility (Teplov, 2019; Chitrakar et al., 2024). Studies highlight the role of colour schemes in cultivating perceptions of stability, information organisation in managing cognitive load, and consistency in navigation patterns in reducing learning barriers (Hick, 1952; Schwartz, 2004; Yablonski, 2024). The literature also incorporates theoretical perspectives such as mental models and Gestalt principles to explain how interface alignment with user expectations reduces friction and facilitates smoother engagement (Gentner & Stevens, 2014). Importantly, scholars link high-quality UI design with enhanced user trust, demonstrating that when consumers perceive systems as reliable, secure, and easy to use, their willingness to engage deepens (Casaló et al., 2024; Kumarasinghe, 2024). This body of work is particularly relevant because it positions UI as the primary touchpoint where users form judgements about institutional credibility, a key factor in engagement with AI-driven services.

Finally, the literature converges on consumer engagement and trust as outcomes shaped jointly by AI functionality and UI design. Engagement is conceptualised across behavioural, affective, and cognitive dimensions, ranging from feature adoption and session frequency to satisfaction, perceived value, and continuance intention (Ayomiposi Feyisekemi Akinwale, 2022; Chukwudi et al., 2023). Expectation Confirmation Theory (Oliver, 1980) helps explain how satisfaction emerges when AI-driven services meet or exceed consumer expectations, while institutional theory highlights the importance of security and compliance in building digital trust. Across these studies, trust consistently emerges as both a precondition and outcome of engagement, contingent on perceptions of security, transparency, and usability (Bach et al., 2022; Casaló et al., 2024). Critically, while separate literatures examine AI, UI, and engagement independently, there remains a lack of integrated analysis exploring how specific AI features and UI elements interact to influence trust and engagement. This gap underscores the need for research that bridges these domains, providing both theoretical insight and practical implications for the design of AI-powered financial platforms.

2.3 Theoretical Frameworks for AI and UI in Banking

Understanding how users interact with AI-powered banking applications requires drawing upon multiple theoretical perspectives (further discussed below in Chapter 3) that span behavioural, cognitive, and strategic domains. At the adoption stage, the Technology Acceptance Model (TAM) (Davis, 1989) provides a foundational explanation, emphasising that perceived usefulness and ease of use are decisive in shaping technology uptake (Ghali, 2021). This is complemented by Expectation Confirmation Theory (ECT) (Oliver, 1980), which explains continuance intention: when AI features meet or exceed expectations, satisfaction and ongoing use are reinforced (Puneett Bhatnagr and Rajesh, 2024; Ghali, 2021). Perceived Anthropomorphism (PAI) (Urquiza-Haas and Kotrschal, 2015) adds a further dimension by showing how human-like qualities in AI can strengthen trust and foster emotional engagement (Hari, Iyer and Sampat, 2021). From a strategic angle, the Resource-Based View (RBV) positions AI capabilities as distinctive, hard-to-replicate assets that can generate sustainable competitive advantage (Barney, 1991; Pamisetty, 2025; Xu et al., 2024). Similarly, Rogers' Diffusion of Innovations (DOI) Theory (1995) highlights that the perceived relative advantage and compatibility of AI features are central to determining adoption rates (Hari, Iyer and Sampat, 2021). At the technical core, the Theory of Neural Networks explains the operational foundation of AI applications, enabling functions such as fraud detection and personalised recommendations (None Olawale Olowu et al., 2024; Pamisetty, 2025).

Parallel to AI, the evolution of User Interface (UI) design has shifted from being a functional necessity to a strategic differentiator (Kreger, 2023; Paneru et al., 2024). Institutional Theory (DiMaggio and Powell, 1983) suggests that financial institutions increasingly adopt sophisticated UI/UX practices not only for operational efficiency but also to align with industry norms and strengthen legitimacy. The cognitive dimension of design effectiveness is illuminated by theories such as Mental Models (Gentner and Stevens, 2014), which stress that intuitive design emerges when interfaces align with users' existing cognitive frameworks (Chitrakar et al., 2024). Similarly, Gestalt principles guide the perceptual organisation of visual elements, ensuring coherence and clarity. Navigation and decision-making are explained by Hick's Law (1952) and the Paradox of Choice (Schwartz, 2004), both of which argue for streamlined pathways to minimise decision latency and reduce user anxiety. Jakob's Law (Yablonski, 2024) further reinforces the importance of familiarity, suggesting that consistency with other digital platforms enhances usability and trust. Finally, the E-S-QUAL model (Parasuraman, Zeithaml and Malhotra, 2005) provides a service-quality perspective, demonstrating how UI influences perceptions of efficiency, responsiveness, and privacy.

Synthesising these perspectives, this study adopts an integrated framework where AI features and UI design elements operate as external stimuli within the user experience. Cognitive and behavioural theories such as ECT, PAI, Mental Models, and Hick's Law help explain the internal processes through which users interpret these stimuli, shaping perceptions of usefulness, satisfaction, and trust. These psychological outcomes, in turn, guide user responses, observable in engagement behaviours such as continuance intention, feature adoption, and session frequency. Meanwhile, broader strategic theories such as RBV and DOI provide the organisational context, explaining why and how financial institutions implement these technologies. Taken together, this framework facilitates a holistic exploration of how AI integration and UI design collectively influence consumer engagement in digital banking ecosystems.

2.4 Empirical Studies on UI, AI, and Trust

Empirical research consistently highlights the importance of user interface (UI) design in fintech adoption and consumer behaviour. Studies have found that specific design elements, such as the use of warm colors (e.g., blue and green) in UI design, can evoke trust, while overly complex designs and usability issues, including slow loading times and difficult navigation, deter engagement (Mavri and Ioannou, 2006; Chitrakar et al., 2024; Teplov, 2019). Furthermore, a range of studies confirms that dynamic and personalized UI elements, such as gamification with reward systems and progress tracking, significantly increase user satisfaction and retention (Dillon and Williams, 2024; Cheng, 2025; Liu et al., 2024; Kreger, 2023; Runsewe et al., 2024).

A growing body of research also demonstrates the impact of AI features on consumer engagement. Empirical findings show that personalized AI recommendations enhance engagement, while a lack of transparency in AI decision-making can reduce trust (Rohit et al., 2025). Studies on perceived AI characteristics such as animacy and intelligence confirm that they can lead to increased user satisfaction and long-term usage intentions (Puneett Bhatnagr and Rajesh, 2024). Additionally, AI-driven tools like chatbots and predictive analytics have been found to positively influence customer engagement by improving efficiency, providing personalized experiences, and enhancing security, all of which contribute to user trust and a willingness to engage (Hari et al., 2021; Koti, 2024; Pamisetty, 2025; Aziz and Andriansyah, 2023).

The cumulative evidence from these studies suggests that trust is established through both explicit security measures and the implicit assurance conveyed by a professional and intuitive interface. This relationship is particularly pronounced in digital banking, where users must balance convenience with risk perception. Despite these individual insights, few studies have examined how UI and AI features interact to synergistically shape engagement in banking apps. This study aims to fill that gap by analyzing their combined effects.

2.5 Research Gap

The above reviewed empirical literature collectively demonstrates a clear positive relationship between well-designed UI/UX, the effective implementation of AI features, and various aspects of consumer engagement, satisfaction, and trust in digital banking. Studies have empirically validated the importance of UI aesthetics, usability, and user-centric design principles in driving user motivation and adoption. Similarly, the benefits of AI-powered personalisation, efficiency, and predictive capabilities in enhancing customer experience and influencing continuance intention have been empirically established. Trust and security emerge as crucial mediating factors, with empirical evidence showing their direct influence on consumer commitment and engagement.

However, a notable empirical gap exists in comprehensively understanding the combined correlational impact of specific UI design elements (e.g., colour palette, information density, gamification) and specific AI tool features (e.g., savings recommendations, fraud alerts, spending categorisation) on consumer engagement. While individual components have been studied, the integrated effect, particularly through a correlational lens that quantifies these relationships and explores their interplay, remains less explored in a single empirical study. This research aims to fill this gap by empirically investigating these combined effects, enriching the understanding of human-AI interaction in the financial sector and providing actionable insights for fintech product development.

Chapter 3: Methodology

This study addresses a critical gap in understanding how User Interface (UI) design and Artificial Intelligence (AI) features jointly shape consumer engagement in digital banking applications. Although prior research has demonstrated that effective interfaces enhance satisfaction (Zhang et al., 2021) and that AI can deliver personalised and efficient services, the two dimensions are often treated in isolation. This fragmented approach overlooks the fact that user experience in banking apps is inherently shaped by the interplay between visual design, functional transparency, and trust in AI-driven processes.

The research problem, therefore, lies in the absence of integrated empirical evidence on how specific UI elements (such as colour schemes, layout intuitiveness, and gamification) and AI functionalities (usefulness, personalisation, transparency) combine to influence trust and sustained engagement. This is particularly pressing in financial contexts where engagement is not merely a matter of convenience but a determinant of consumer confidence and loyalty. Existing models of gamification (Hamari et al., 2014), AI trust factors (Smith, 2023), and interface psychology (Zhang et al., 2021) highlight these variables individually but stop short of examining their cumulative effect in high-stakes digital environments.

Focusing on these underexplored intersections is essential for two reasons. First, it responds directly to scholarly calls for more nuanced, correlational analyses that move beyond siloed perspectives of design or technology. Second, it offers practical insight for fintech developers tasked with designing systems that are not only efficient but also trusted and engaging. By positioning UI and AI features as complementary determinants of user experience, this research justifies its focus as both theoretically necessary and practically significant.

A self-administered online questionnaire was employed as the principal method of data collection in this study. This instrument was selected as the most suitable approach for several reasons. First, it facilitated the efficient gathering of quantitative data from a geographically dispersed sample, a requirement that was particularly important for conducting the correlational analysis underpinning the research objectives (RQ1, RQ2). Second, the use of structured Likert-scale items enabled the standardized assessment of complex constructs such as perceived trust and usability, thereby supporting the rigorous statistical testing of the study's hypotheses (H1, H2, H3). The questionnaire was carefully designed to operationalise the study's central concepts and objectives. Each section was structured systematically around the core variables identified in the literature review, namely user interface (UI) design elements, artificial intelligence (AI) features, and consumer engagement and trust, ensuring that the data collected directly addressed the research questions and hypotheses.

Although the inherent limitations of self-reported data were recognised, including the potential for social desirability bias, steps were taken to minimise these issues. Anonymity was assured for all participants, and reverse-coded items were incorporated to enhance response reliability. Furthermore, the inclusion of open-ended questions alongside quantitative scales provided an important qualitative dimension, capturing nuanced user perspectives and enriching the statistical findings. This mixed-methods design thus offered a balance between generalisable quantitative insights and contextually rich qualitative data, making it a methodologically sound and pragmatic choice for the scope of the present study.

3.1 Research Questions and Hypotheses

3.1.1 Research Questions

1. How do UI design elements (color palette, information density, gamification) influence consumer engagement in AI-powered banking apps?
2. What is the relationship between AI-driven features (savings recommendations, fraud alerts, spending categorization) and user engagement?
3. How do user perceptions of trust and usability mediate the impact of UI and AI features on engagement?

3.1.2 Hypotheses

H1: Simplified UI designs (low information density, intuitive layouts) positively correlate with higher engagement.

H2: AI features that enhance personalization (e.g., tailored savings tips) increase user engagement.

H3: There is a significant positive relationship between UI design elements and AI features in AI-powered banking applications.

3.2 Theoretical Framework

The research design for this study was directly shaped by a theoretical framework that synthesizes concepts from information systems, psychology, and management. This led to an effective process of transforming abstract ideas into specific, measurable variables for the survey, ensuring the quantitative findings are firmly connected to scholarly discourse.

These theoretical lenses provide a robust framework for understanding the complex relationships between UI Design Elements, AI Tool Features, and Consumer Engagement in AI-powered Banking Applications.The first three basic frameworks that determine an understanding of AI Features and UI Design Elements and how they influence Consumer Engagement are:

The Technology Acceptance Model (TAM) (Davis, 1989) suggests that perceived usefulness and ease of use determine user adoption of technology. In AI-powered banking, UI design and AI functionalities may influence these perceptions (Ghali, 2021).

The Cognitive Load Theory introduced by Sweller, 1988 posits that excessive information density in UI design can overwhelm users, reducing engagement. This theory helps assess how design simplicity enhances usability (Schwartz, 2004).

Affordance Theory by Norman in the year 1999 argues that UI elements should intuitively guide user interactions. Well-designed affordances in banking apps may improve engagement by making AI features more accessible (Teplov, Danii, 2019).

When studied in detail, the theoretical framework can be further examined specifically into each variable and how enhancement of each variable has been supported and developed using a few theoretical understandings and ideas.

3.2.1 *In relation to AI in banking apps*

The Resource-Based View (RBV) provides a fundamental understanding of AI's role in banking. According to RBV, a company's distinctive and valued resources and competencies are the source of its long-term competitive advantage (Barney, 1991; Pamisetty, 2025; Xu et al., 2024). AI capabilities (such as advanced algorithms, data processing power, and predictive analytics) are essential assets in the context of AI-powered banking because they allow banks to provide unique services, boost operational effectiveness, and improve customer experience (Pamisetty, 2025; Xu et al., 2024). Developing and utilising these resources to acquire and preserve market leadership is the ongoing process of AI's progress in banking (Koti, 2024).

Another theory that can explain the enhancement and advancement of AI is the Diffusion Of Innovation Theory (DOI), introduced by Rogers in 1995. According to Rogers, this theory talks about how and on what rate new ideas and technologies travel through a population through a social system (Wilkening, 1963). It focuses on how an idea, object or practice is perceived and communicated through various channels. The adoption of AI-powered features such as savings recommendations, fraud alerts, and spending categorisation is largely influenced by consumers' perceptions of attributes including relative advantage, compatibility, complexity, trialability, and observability (Hari, Iyer and Sampat, 2021). In this context, banks, acting as key innovators, aim to support the diffusion of these technologies by designing features that are easy to understand and integrate into individuals' routine financial behaviours.

Several psychological theories can support and highlight user interactions with AI. Expectation Confirmation Theory (ECT), originally proposed by Oliver (1980), offers a valuable framework for understanding the adoption and continued use of artificial intelligence (AI) in banking applications (Pinski and Benlian, 2024; Ghali, 2021). According to ECT, user satisfaction and the intention to continue using a technology are influenced by the extent to which and how their initial expectations are confirmed through actual performance. When AI-driven features within banking apps meet or exceed user expectations, they tend to foster a sense of satisfaction, which in turn encourages ongoing engagement (Puneett Bhatnagr and Rajesh, 2024). This theory is particularly useful in explaining why users are likely to remain committed to using AI-integrated financial services and build an initial trust towards AI.

In addition to expectation confirmation, the concept of Perceived Anthropomorphism (PAI) plays an important role in shaping how users relate to AI systems. PAI refers to the tendency to attribute human-like qualities, emotions, or intentions to non-human entities, including AI technologies (Urquiza-Haas and Kotrschal, 2015). Within the context of banking, AI features such as conversational chatbots or personalised, empathetic advice can evoke a human-like presence, potentially enhancing user trust and emotional engagement (Hari, Iyer and Sampat, 2021). The degree to which users perceive AI as anthropomorphic can influence their sense of trust, particularly when interacting with AI for sensitive or complex financial tasks.

The broader understanding of user acceptance and sustained interaction with AI technologies can also be informed by related constructs from both ECT and the Technology Acceptance Model (TAM). Concepts such as Confirmation, Perceived Usefulness (PU), E-Satisfaction, and Continuance Intention are particularly relevant in this regard. Perceived Usefulness, as defined by (Davis, 1989), refers to the extent to which a user believes that a given technology will enhance their performance. In the context of AI-enabled banking, users are more inclined to adopt and continue using features they perceive as beneficial, such as those that save time, provide insights, or streamline financial management(Puneett Bhatnagr and Rajesh, 2024). Hence, building a belief that their banking experience can be made accessible, efficient and effective through the integration of AI while also knowing that their data is kept secure and they are only presented with information that is relevant to their financial routine.

E-Satisfaction, or the user's overall satisfaction with the AI, enhancing banking experience, is a critical determinant of continuance intention, the likelihood of sustained usage over time (Ayomiposi Feyisekemi Akinwale, 2022; Ghali, 2021). When users experience a positive interaction with AI tools, it reinforces their willingness to maintain long-term engagement with the application, through a sense of loyalty that they build over time and experience, which streamlines well into the aims and objectives of most fintech companies.

Lastly, while not a behavioural framework, the Theory of Neural Networks underpins the functionality of many AI features within banking platforms. These systems rely on complex algorithms that mimic cognitive learning processes found in the human brain, enabling the AI to adapt, learn from data, and deliver personalised services (None Olawale Olowu et al., 2024; Pamisetty, 2025). Acknowledging this technical foundation can help contextualise the perceived intelligence of AI by users and illuminate how such systems are able to deliver tailored recommendations, detect fraudulent activity, and assist with spending categorisation, all of which can directly influence Consumer engagement and trust.

Although the present study concentrates on the Consumer perspective and dimensions of artificial intelligence (AI) in banking applications, the theoretical framework recognises that the overall effectiveness of these features is fundamentally dependent on their technical implementation. Core technologies such as machine learning algorithms, natural language processing (NLP) for chatbot interactions, and predictive analytics for delivering personalised recommendations and detecting fraudulent activity form the backbone of AI functionality (None Olawale Olowu et al., 2024; Pamisetty, 2025). These technical components enable the seamless and intelligent user experiences that drive adoption and continued engagement.

3.2.2 In relation to UI Design Elements in banking apps

As understood above that AI features are theorised to enhance user engagement, the user interface functions as the primary channel through which this interaction is realised. Accordingly, this section examines the theoretical foundations of UI design. Within this section, UI design represents the second core pillar of the framework, illustrating how design decisions can either promote seamless engagement with AI tools or introduce barriers that diminish their perceived value.

The evolution of UI design in banking has moved from functional necessity to a strategic imperative for user engagement and competitive differentiation (Kreger, 2023; Paneru et al., 2024). Early online banking interfaces were often clunky and complex (Mavri and Ioannou, 2006), but with advancements in technology and a greater focus on user-centric design, UIs have become more intuitive and aesthetically pleasing (Chitrakar et al., 2024; Teplov, Danii, 2019). The enhancement of UI in banking apps is driven by the desire to improve usability, accessibility, and overall user experience. This involves adopting user-centric design principles, iterative testing, and incorporating modern design trends to create engaging and efficient interfaces. Generative AI is also playing a role in automating and augmenting UI design workflows (None Olawale Olowu et al., 2024).

To achieve the above aims and objectives of the implementation of UI design elements, an understanding of a theoretical framework is very important to evolve the elements according to the user expectations and to build user engagement.

Institutional Theory (DiMaggio and Powell, 1983) provides a useful lens for understanding why financial institutions adopt advanced user interface (UI) and user experience (UX) practices. Beyond improving operational efficiency, organisations often implement such design standards to gain legitimacy and align with evolving industry norms.
As user-centric design becomes increasingly central to the fintech landscape, banks are compelled to integrate sophisticated UI features to appear modern, competitive, and trustworthy in the eyes of consumers. Complementing this institutional perspective is the concept of mental models (Dedre Gentner, Albert L. Stevens, 2014)), which plays a foundational role in effective UI design.
Users develop internal representations of how systems should function based on their past experiences, and aligning interfaces with these mental models enhances intuitiveness, reduces cognitive load, and facilitates ease of use (Chitrakar et al., 2024).

Gestalt psychology further informs UI design by offering principles that guide visual organisation and user attention. Techniques such as proximity, similarity, continuity, and closure help create interfaces that are coherent and easy to navigate, particularly important in managing the often complex information architecture of banking applications (Chitrakar et al., 2024).

Cognitive processing efficiency is also addressed through Hick's Law (Hick, 1952), which posits that decision-making time increases with the number of available options. For financial applications, this implies that limiting or logically organising choices can significantly enhance usability and user satisfaction.

The Paradox of Choice (Schwartz, 2004) builds on this by suggesting that while offering options is generally beneficial, an overabundance can lead to anxiety, decision fatigue, and eventual disengagement. Thus, striking the right balance in feature availability and interface simplicity is essential.

Jakob's Law underscores the importance of design consistency, noting that users draw expectations from other frequently used digital platforms (Yablonski, 2024). In the context of banking, consistent navigation structures, iconography, and interaction patterns not only reduce the learning curve but also foster trust and a sense of familiarity (Kreger, 2023).

Lastly, the E-S-QUAL model (Lin, 2025) offers a comprehensive framework for evaluating the quality of electronic services, including mobile banking applications. The model focuses on key dimensions such as system efficiency, availability, fulfilment, and privacy, all of which are deeply influenced by UI design choices (Lin, 2025). When thoughtfully implemented, these elements can significantly enhance user satisfaction, trust, and continued engagement with digital financial platforms.

3.2.3 In relation to Consumer Engagement and Trust in banking apps

Consumer responses to artificial intelligence (AI) in banking are shaped by both cognitive and perceptual factors, as explained above. Expectation Confirmation Theory (ECT) posits that user satisfaction and continued engagement are influenced by the extent to which initial expectations regarding AI performance are met or exceeded, while Perceived Anthropomorphism (PAI) highlights the role of human-like attributes in shaping user interaction with AI systems (Kartikey Koti, 2024). The strategic implementation of AI in banking aims to enhance customer experience, increase operational efficiency, and deliver personalised financial solutions.

Closely related to this is the role of user interface (UI) design, which significantly impacts consumer trust. A secure, private, and user-friendly interface not only facilitates usability but also reinforces perceptions of institutional reliability and safety (Casaló, Luis V. ; Flavián, Carlos ; Guinalíu, Miguel, 2024). When users perceive the UI as well-designed and trustworthy, their confidence in the banking application and, by extension, the financial institution strengthens, fostering deeper engagement and long-term use (Kumarasinghe, 2024; Kreger, 2023).

3.2.4 Influence of use and framework of AI Features and UI Design Elements on Consumer Engagement and Trust

The implementation of artificial intelligence (AI) in banking primarily aims to streamline operational processes, enhance security, and deliver hyper-personalised financial services (None Olawale Olowu et al., 2024; Pamisetty, 2025). Key drivers behind this adoption include fraud prevention, effective risk management, automated customer support, and the provision of tailored financial advice; each of these contributes to improved customer satisfaction and long-term loyalty (Kartikey Koti, 2024).

Parallel to AI integration, the development of sophisticated user interfaces (UI) serves as a strategic tool to foster user engagement, cultivate trust, and establish competitive differentiation within the fintech sector (Kreger, 2023). These efforts are guided by User-Centred Design (UCD) frameworks, which emphasise the active involvement of end users throughout the design process. By prioritising user needs, expectations, and feedback, UCD methodologies help ensure that the final product delivers both functional value and a positive user experience (Liu et al., 2024; Teplov, Danii, 2019).

A central focus of artificial intelligence (AI) in banking is also the ability to understand and predict user behaviour patterns in order to meet and exceed customer expectations. This is achieved through the deployment of hyper-personalised rewards and benefits programmes, as well as adaptive interfaces that respond to real-time user data to optimise engagement (Bach et al., 2022; Liu et al., 2024).

The overarching aim is to enhance user experiences by providing convenience, efficiency, and contextually relevant financial guidance (Menezes, Kavyashree K and Naik, 2024). Although the technical implementation of user interfaces (UI) is not the primary focus of this study, its role remains critical. Effective UI delivery relies on robust front-end development, responsive design principles that ensure usability across devices, and seamless integration with backend systems that support AI functionality. These technical foundations are essential for maintaining the continuity and quality of the user experience (Chitrakar et al., 2024).

3.2.5 The framework for Consumer Engagement and Trust

This study integrates a range of theoretical perspectives to construct a comprehensive framework for analysing consumer engagement within AI-powered banking applications. The independent variables, specifically UI Design Elements and AI Feature functionalities, are conceptualised as stimuli that influence user perceptions and behaviours. Theories such as Expectation Confirmation Theory, Perceived Anthropomorphism, Mental Models, Gestalt Psychology, Hick's Law, the Paradox of Choice, and Jakob's Law are employed to explain the cognitive and emotional processes through which users interpret these stimuli.

This internal processing corresponds to the "organism" component within the Stimulus-Organism-Response model, (Mavri and Ioannou, 2006), and leads to key outcomes including perceived usefulness, satisfaction, and trust. These outcomes subsequently inform the dependent variable of consumer engagement, which is operationalised through measures such as continuance intention, session frequency, feature adoption, and duration of use.

In addition, the Resource-Based View and Diffusion of Innovations theories provide a strategic and contextual foundation, offering insights into the organisational motivations for adopting and implementing these technological innovations within the banking sector. By integrating cognitive, behavioural, and strategic dimensions, this framework supports a holistic examination of how the design of the user interface and the intelligence of AI features collectively shape the user experience and influence sustained interaction with digital banking platforms.

In conclusion, the theoretical framework in this study functioned as more than an academic backdrop. It provided the foundation for designing a research instrument that was both conceptually rigorous and practically applicable. Each theory directly informed the questionnaire's structure and content as well as the process of analysis to attain the aims and objectives of the stufy. For example, Hick's Law and the Paradox of Choice guided the development of questions on information density, while Gestalt principles and Jakob's Law shaped items assessing visual design and navigation. To capture perceptions of AI, the Technology Acceptance Model (TAM) and Expectation-Confirmation Theory (ECT) were used to frame items on perceived usefulness and satisfaction, complemented by Perceived Anthropomorphism to explore user comfort. The Resource-Based View further justified the focus on these features as potential sources of competitive advantage. This intentional integration of theory into survey design ensured that both the Likert-scale measures and qualitative prompts effectively operationalised the core concepts, thereby enhancing the validity of the study's findings.

3.3 Research Strategy

This study adopts a mixed -methods approach to examine the relationship between UI design elements, AI features, and consumer engagement. The choice of this design was intentional and explicitly influenced by the theoretical framework outlined in Chapter 3. 2. The initial quantitative phase was structured to test hypotheses grounded in established theories. Through the questionnaire, key principles from the Technology Acceptance Model (TAM) and Perceived Anthropomorphism were operationalised into measurable v ariables, enabling statistical analysis of the relationships between UI design, AI features, and engagement.

The subsequent qualitative phase added depth by capturing the in -depth perceptions and contextual insights of users. Analysis of open -ended responses provided critical understanding of trust and usability which are also the key concepts as highlighted in t he study's theoretical framework. This sequential design, beginning with a broad quantitative assessment and progressing to a focused qualitative analysis, ensured a comprehensive investigation. It combined the rigour of statistical analysis with the richn ess of lived experiences, thereby offering a more holistic understanding of the research problem and gap.

3.4 Sampling

According to the requirements of the study, the target audience consisted of the individuals who actively used online banking apps. The sample of the study consisted of 110 individuals and the age range from 18 -70. Online data collection methods were used to approach these participants, via social media. The sampling method used was convenient sampling which is a non -probability sampling method.

3.4.1 Inclusion criteria:

- Those who actively engage with AI -powered banking tools
- Those who are above the age of 18
- Those who have used the app for at least 3 months

3.4.2 Exclusion criteria:

- Those who do not actively engage with AI -powered banking tools
- Those who are below the age of 18
- Those who have used the app for less than 3 months

3.5 Procedure

After the proposal was approved by the Ethics committee of the University of Stirling and appointed supervisor, individuals were approached for data collection. The collection of data was done keeping in mind the demographic details of the participants and the inclusion criteria of the research. Data was collected through an online questionnaire, via google forms. The survey was sent to the participants through social media and Whatsapp.
Upon completion of the data collection, the gathered data was compiled on an Excel sheet and was saved in a password -protected laptop which was only accessible by the researcher, to adhere to the confidentiality policies. The data was further analysed using Jamovi software for descriptive and inferential statistics (Jamovi, 2022). Each participant was asked to give their informed consent to participate in the research. Upon completion of the study, the data will be stored for five years on University OneDrive, for publication purposes.

3.6 Ethical considerations

3.6.1 Informed Consent

Before data collection, researchers will get participants' informed permission by outlining the study's objectives, methods, potential risks, and advantages. This way the participants will have a clear understanding of what their contribution will entail and have the right to withdraw at any time.

3.6.2 Confidentiality and Anonymity

Participants will be provided with guarantees that their identities will be kept secret and that no one outside the supervising committee and the researcher will have access to their data. Personal and delicate information will be handled with the highest discretion and anonymity. It shall be ensured that all information gathered is kept safe and that only the researcher has access to.

3.6.3 Voluntary Participation

Participants will be free to decide whether or not to take part in the study, and they won't be subjected to any compulsion or pressure. They are free to reject participation without incurring any consequences and to leave the research at any time.

3.7 Measures

Data was collected using a self-administered online survey with the help of 5 point Likert scale, designed in such a way that it captures both Quantitative perceptions and Qualitative experiences. The survey sections was designed in a way that it targets the UI Design Elements and AI Features (Independent Variables) and Consumer Engagement and Trust (Dependent Variable).

3.7.1 UI Design Elements (IV 1) This variable assessed participants' perceptions of the user interface's visual and interactive design, including the effectiveness of the color palette, the clarity and organization of information density, and the influence of gamification elements. It was measured using a multi-item scale and reverse coding, comprising 10 questions, each rated on a 5-point Likert scale ranging from 1 ('Strongly Disagree') to 5 ('Strongly Agree') or vice versa under reverse coding. The sum scores for this variable ranged from 14 to 50.

3.7.2 AI Features (IV 2) This variable evaluated participants' perceptions and usage of AI-driven features in banking applications, focusing on key functionalities such as savings recommendations, fraud alerts, and spending categorization. The construct was measured using a 5-item scale with reverse-coded items, each rated on a 5-point Likert scale (1 = 'Strongly Disagree' to 5 = 'Strongly Agree' or vice versa for reverse coding). Total scores for this variable ranged from 9 to 25.

3.7.3 Consumer Engagement and Trust (DV): This variable measured participants' overall engagement with and trust in AI-powered banking applications, capturing dimensions such as usage frequency, feature adoption, perceived utility, satisfaction levels, and confidence in the AI system's reliability and security. The construct was assessed using a 5-item Likert scale (1 = "Strongly Disagree" to 5 = "Strongly Agree"), with total scores ranging from 13 to 35.

3.8 Data Analysis

The data was converted into an excel sheet after collection. The relationship between variables, UI Design Elements, AI Features and Consumer Engagement and Trust was analysed using Jamovi. Correlation and Regression analysis were conducted after the colle ction data to analyse if there is a significant relationship between the variables. Descriptive and Inferential statistics were also used to assess the data collected in the Excel Sheet. The result has been discussed in the research paper.

Collected data was organised and analysed using Jamovi. Descriptive statistics along with the Shapiro -Wilk test of normality was used. Following this analysis, non - parametric statistical analysis like Spearman's correlation and Linear Regression analysis were adopted. Stepwise regression analysis was employed to test if the Independent variables, UI Design Elements and AI Features are a possible predictor of Consumer Engagement and Trust (Dependent Variable). Additionally, Collinearity statistics was adopte d to assess the variance and independence level of the UI Design Elements and AI Features. Visual presentation of Q -Q plots of standardised residuals to assess the normality of error terms and the influence on the Consumer Engagement and Trust (Dependent V ariable).

3.8.1 Qualitative Data Analysis

A thematic system approach was used to analyse the responses from the open - ended questions from the questionnaire. This involved repeated reading of all qualitative responses in order to gain an overall understanding and familiarisation. The data was then coded, to identify initial patterns and ideas within the data and assign preliminary codes. Which was followed by generating themes and categorising codes into broader aspects of participant's experiences and ideas. The emergent themes were reviewed and re fined to verify their alignment with the dataset and relevance to the research objectives. Through this process, each theme was precisely delineated and assigned a clear, descriptive label to capture the participant's perceptions and experiences.

Chapter 4: Case study: Based on the annual statement of Wise (2024)

To contextualise the theoretical discussions on UI design elements, AI-driven features, and consumer engagement, this section provides a brief case study of Wise, a prominent digital banking application, drawing insights from its 2024 annual report. Wise, an established global business, aims to achieve "Money Without Borders" by offering fast, low-cost, and transparent international money transfer services, simplifying cross-border transactions for millions (Wise, 2024, p. 2-5). Their approach is inherently customer-centric, focusing on building products and features that make moving and managing money across borders easier, faster, more transparent, and cost-effective for everyone (Wise, 2024, p. 7).

Wise's interface is meticulously crafted to reflect its core principles: speed, transparency, ease of use, and affordability (Wise, 2024, p. 7). The design is clean, uncluttered, and intuitive, making complex international money transfers feel simple rather than overwhelming. For example, Wise explicitly states it's "upfront about what our customers pay. No asterisks, small print or hidden fees" (Wise, 2024, p. 15), directly addressing a common frustration users experience with hidden charges in traditional banking. This transparent approach to information presentation aligns with the principles of Hick's Law and the Paradox of Choice, as it reduces cognitive load by presenting clear, concise information, thereby improving decision-making efficiency. The uncluttered nature of the interface also reflects principles of Gestalt Psychology, where visual simplicity and clear grouping of information enhance user comprehension and attention.

While Wise does not explicitly feature traditional gamification elements like points or badges, its emphasis on "speed" and "instant" transfers (62% of transfers arrive in less than 20 seconds, Wise, 2024, p. 14) can create a subtle sense of achievement and efficiency for users. This rapid gratification functions as a form of intrinsic reward, subtly influencing user engagement and satisfaction, akin to the positive reinforcement sought in gamified experiences.

The information presented on the app is highly specific and user-relevant, demonstrating an optimal approach to information flow and reducing cognitive load. Their upfront approach to easy and quick transactions exemplifies effective information density, ensuring users are not overwhelmed but rather guided efficiently through their tasks. When it comes to their design aesthetics, the graphics are a combination of blue, white, and greys. This simplicity of a colour palette makes the functioning of the app visually appealing and uncluttered, encouraging the user's attention to critical information, reinforcing a sense of trust and professionalism (Wise, 2024, p. 7). This visual consistency and clarity also align with Jakob's Law, as users familiar with clean, modern interfaces will find Wise's design intuitive and trustworthy.

Overall, the design elements of Wise collectively project reliability, commitment, and transparency to its users, which directly impacts their engagement globally, as evidenced in the report. This demonstrates how effective UI design, informed by psychological principles, contributes to positive consumer responses and sustained usage.

Wise also extensively leverages machine learning and AI tools within its infrastructure to enhance efficiency, security, and customer experience. The company employs a "proprietary machine learning approach to fighting financial crime" (Wise, 2024, p. 18), processing over a million documents a month with this technology. This continuous investment ensures robust fraud detection and compliance, which is vital for maintaining user trust in financial transactions (Wise, 2024, p. 17, 69). This application of AI directly supports the Resource-Based View, as advanced fraud detection capabilities become a valuable, inimitable resource for Wise, enhancing its competitive position.

The company actively invests in AI to "automate manual processes and provide a better end-to-end customer experience" (Wise, 2024, p. 17). This automation contributes to the perceived "ease" and "speed" of the service, directly impacting user satisfaction. This aligns with Perceived Usefulness (PU) and Expectation Confirmation Theory (ECT), as the AI features deliver tangible benefits that meet or exceed user expectations for efficiency.

In terms of risk management and fraud prevention, Wise employs a three-line defence model, wherein operational teams manage day-to-day risks, audit teams oversee controls, and compliance functions provide oversight (Wise, 2024, p. 69). They use advanced AI tools for fraud detection and conduct stress level tests (like simulating recessions or cyberattacks) to confirm the company’s viability for at least three years (Wise, 2024, p. 69). This robust integration of AI for security and operational resilience directly contributes to user trust, a critical antecedent to engagement, as users feel more secure entrusting their finances to a technologically advanced and secure platform.

Wise's strategic integration of intuitive UI design and advanced AI features directly translates into strong consumer engagement metrics. The company reported a 29% increase in active customers, reaching 12.8 million in FY2024, with over 3 million new customers joining during the year (Wise, 2024, p. 4, 21). A significant proportion of customers, nearly half of personal users and 60% of business users, have adopted the Wise Account, indicating high feature adoption (Wise, 2024, p. 5, 37). These figures empirically demonstrate the positive correlation between well-implemented UI and AI features and high levels of consumer engagement, including session frequency and feature adoption, reinforcing the theoretical links to Continuance Intention and E-Satisfaction.

In examining the broader empirical landscape of AI-enhanced UX/UI design within the banking sector, recent evidence further underscores the substantial influence of AI on user engagement metrics. A study highlights that an impressive 78% of fintech companies have integrated AI-driven UX/UI solutions, leading to a notable increase in consumer interaction, with a remarkable 41% rise in daily active users due to advanced AI features (Xu et al., 2024). These findings suggest that AI not only enriches the aesthetic and functional aspects of user interfaces but also plays a crucial role in actively engaging users by meeting their evolving preferences and expectations. Banks that effectively incorporate AI functionalities like predictive analytics and conversational interfaces into their UI design can build more intuitive and responsive applications, which align with consumer demands for personalised and frictionless experiences. By leveraging these AI capabilities, financial institutions can strengthen their competitive stance in the fintech landscape, fostering deeper consumer trust and loyalty.

Chapter 5: Research Findings and Discussions

Descriptive statistics (Table 1 below) indicates that the mean score and standard deviation of the variables, UI Design Elements ($M = 35.4$, $SD = 5.41$), AI Features ($M = 15.4$, $SD = 2.83$), and Consumer Engagement and Trust ($M = 24.8$, $SD = 3.92$). The Shapiro-Wilk test suggests that the variables, UI Design Elements (($W = <.001$, $p = 0.927$), AI Features ($W = 0.965$, $p = 0.005$) and Consumer Engagement and Trust ($W = 0.970$, $p = 0.014$) are not normally distributed.

The data being not normally distributed, Spearman's correlation analysis was carried out (Table 2 below) to identify the relationship between the variables. Results indicate a moderately positive relationship between UI Design Elements, AI Features and Consumer Engagement and Trust. There is a significantly moderate positive relationship between UI Design Elements and AI Features ($r = 0.416$, $p < .001$). There is a significantly moderate positive relationship between UI Design Elements and Consumer Engagement and Trust ($r = 0.311$, $p < .001$). There is a significantly moderate positive relationship between AI Features and Consumer Engagement and Trust ($r = 0.469$, $p < .001$).

Linear regression analysis (Table 3 below) demonstrates that there is a significant intercept between UI Design Elements and AI Features and therefore influences Consumer Engagement and Trust ($\beta = 13.1724$, $t = 5.79$, $p < .001$). The F value derived is significantly higher than 4.0, which indicates that the UI Design Elements and AI Features predict the Consumer Engagement and Trust ($F = 17.9$, $p < .001$). The predictors which are UI Design Elements and AI Features show a 25% ($R^2 = 0.250$) directly influence Consumer Engagement and Trust. While AI Features are significantly positive predictor of Consumer Engagement and Trust ($\beta = 0.6231$, $p < .001$), UI Design Elements are not a significantly positive predictor of Consumer Engagement and Trust ($\beta = 0.0573$, $p = 0.437$). This indicates that in presence of the AI Tool Features, UI Design Elements may not contribute significantly to the prediction of Consumer Engagement and Trust. Therefore, AI Features are a strong and independent predictor of Consumer Engagement and Trust.

The linear regression analysis also predicted that for every one-unit increase in AI Features, there is a consecutive increase in units of Consumer Engagement and Trust (0.06231), which also proves that the UI Design Elements will remain constant.

Based on the assumptions checks (Table 4 below), the Variance Inflation Factor (VIF) suggests how much variance of an estimated regression coefficient is inflated due to multicollinearity. The VIF value threshold is between 5-10, while the values of both independent variables are 1.47 and tolerance values as 0.679. This indicates that multicollinearity is not a significant concern, suggesting that the independent variables are not overly correlated with each other allowing an independent effect of each variable.
The Q-Q Plots and Residuals plot also confirmed the non-normality distribution of the data as indicated in the descriptive analysis.

5.1 Qualitative Analysis Results

Thematic analysis was adopted to encode the responses from the open-ended questions from the questionnaire. The questionnaire consisted of two open-ended questions: “What one change would most improve your trust in the app's AI?” and “Describe a situation where the UI design helped or frustrated you”.

“What one change would most improve your trust in the app's AI?”

Participants' suggestions to improve their trust in the app's AI was centered on transparency, security and more human-like interactions. This highlights that there is a need for clarity and risk management in financial apps.

The suggestion about “Transparency and explainability" was observed to be the dominant one. Participants desired to understand the working of AI and the fundamentals behind decision-making of AI. For example, one participant wished for "Increased transparency regarding how the AI makes decisions and a clear explanation of its limitations" (ST, 29). This suggests that there is a lack of clear understanding of how AI makes decision-making and transparency about AI’s limitations.

Another user expressed "mistrust with AI and how reliable it can be," worrying about how AI functions and "how it ensures that my information (and money) is secure" (Irfan Yaqub, 30). This suggests that there is a mistrust issue about data security and unassurance about the reliability of AI. The suggestion for "More knowledge sharing about it" (NLKY, 24) further emphasizes this gap in user understanding, implying that proactive education about AI features could significantly bolster trust.

A direct request for enhanced "Security" (Muhammad Baqir, 26) highlights concerns about security from AI. Participants also linked reliability to practical, real-time functionality, suggesting "Customised suggestions during the transfer process regarding the transection time will enhance the reliability of the AI system" (Irfan Yaqub, 30). The mention of needing "License and registration" (Zarghona Ayub, 35) suggests a desire for accountability and validation of AI tools from Fintech companies.

A direct plea for "More human aspects" (LJL, 23) suggests a desire for less robotic and more intuitive AI interactions, indicating a desire towards more human-like interactions from AI. This preference became apparent when the AI fell short, as evidenced by frustration when the AI "Didn't answer my questions" (Muhammad Baqir, 26).

"Describe a situation where the UI design helped or frustrated you".

A situation when UI design elements helped,

The positive responses under this situation were focused on intuitive navigation and clarity. A clear and intuitive navigation menu enabling "quick access to banking features" (ST, 29) was highly praised. The "transection technique employed by Wise has significantly facilitated the smoothness of the entire operation" (Irfan Yaqub, 30), indicating a well-designed workflow. The convenience of "Scan and pay Ui" (KT, 24) exemplifies effective, streamlined UI elements. This indicates that the consumers prefer easier location and effective utilisation of banking features.

There was also one highlight on the design of specific features, which enhanced user experience. Appreciation for "multiple savings pots and cards" (Sw, 22) indicates that well-implemented, distinct features contribute positively to usability and engagement.

A situation when UI design was frustrating

Negative feedback was observed from the responses which highlighted that UI Design Elements can be complex and lead to Information Density. Participants reported being particularly frustrated by "An overly complex UI with too many nested menus, making simple tasks difficult to complete" (ST, 29). General dissatisfaction with "When contents page is not neat" (Zarghona Ayub, 35) reflects issues with disorganized layouts. This indicates that complex designs and cluttered interfaces make simple tasks very difficult for the consumers. The initial learning curve, where a participant is "just pressing on everything to figure out how everything works" (Irfan Yaqub, 30), suggests a lack of immediate intuitiveness or clear onboarding.

"The absence of an easily accessible Terms And Conditions Form" (SH, 25) can erode trust if crucial details are hard to find. This suggests that lack of clarity and responsiveness leads to confusion and complex process of task completions, which leads to frustrations among the consumers.

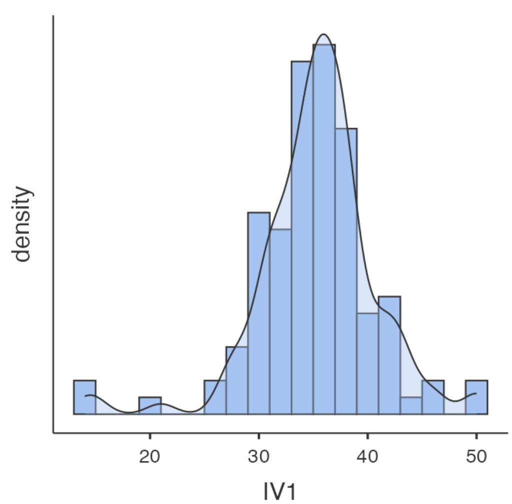
Table 1: Descriptive statistics with Shapiro-Wilk of Normality

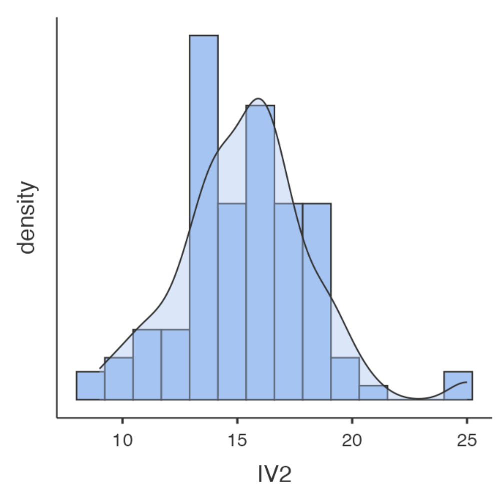
Statistic	IV1	IV2	DV

N	110	110	110
Mean	35.4	15.4	24.8
Median	36	15.5	25
Standard Deviation	5.41	2.83	3.92
Variance	29.3	8.03	15.3
Minimum	14	9	13
Maximum	50	25	35
Skewness	-0.74	0.42	-0.33
Std. Error of Skewness	0.23	0.23	0.23
Kurtosis	3.7	1.4	0.51
Std. Error of Kurtosis	0.46	0.46	0.46
Shapiro-Wilk W	0.93	0.97	0.97
Shapiro-Wilk p	< .001	0.005	0.014

Note: IV1= UI Design Elements, IV2= AI Feature, DV= Consumer Engagement and Trust

Plots





DV

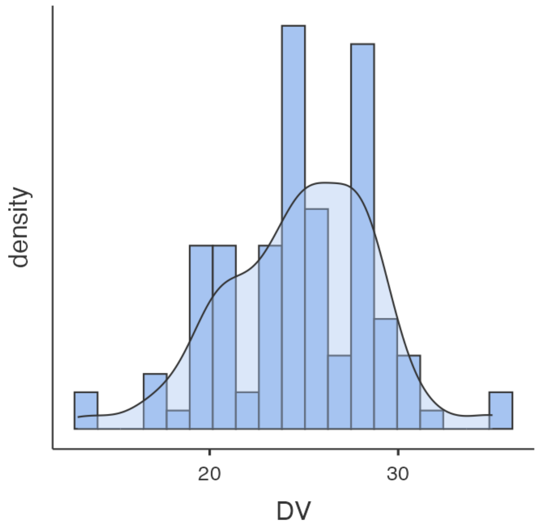


TABLE 2:

Relationship between UI Design Elements, AI Features and Consumer Engagement and Trust.

Variable	1	2	3
UI Design Elements (IV1)	—		
AI Features (IV2)	0.416***	—	
Consumer Engagement and Trust (DV)	0.311***	0.469***	—

Note: All correlations are significant at p<.001. The degrees of freedom for all tests is 108, with a total sample size of N= 110.

***p<.001

Plot 2: Correlation Matrix

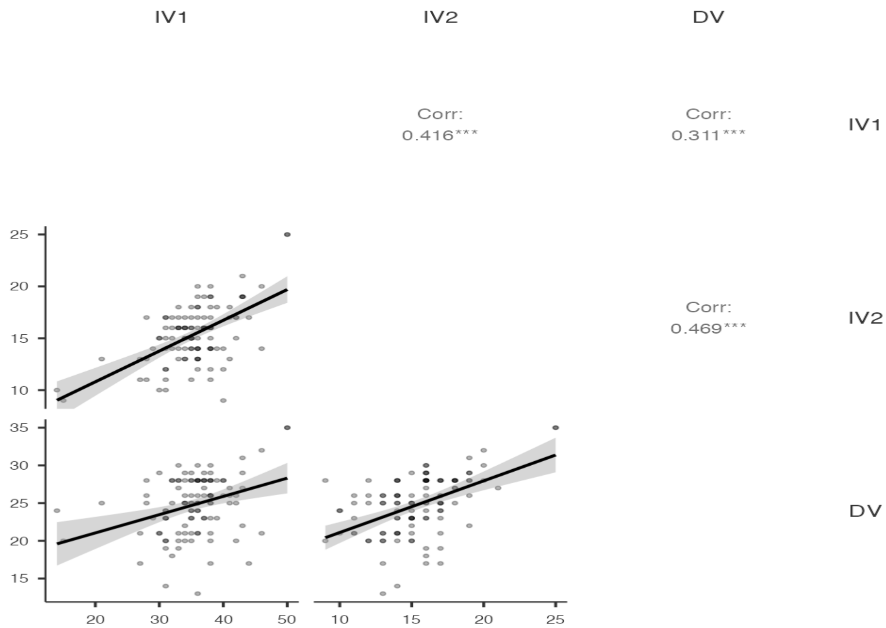


TABLE 3:
Impact of UI Design Elements and AI Features on Consumer Engagement and Trust

Model	R	R^2	Adjusted R^2	F	df1	df2	p-value
1	0.500	0.250	0.236	17.9	2	107	<.001

Note. Models estimated using sample size of N=110

Model Coefficients - DV

Predictor	Estimate	SE	t	p
Intercept	13.1724	2.2743	5.792	<.001
IV1	0.0573	0.0735	0.780	0.437
IV2	0.6231	0.1403	4.442	<.001

TABLE 4: Variance Inflation Factor

Assumption Checks; Collinearity Statistics

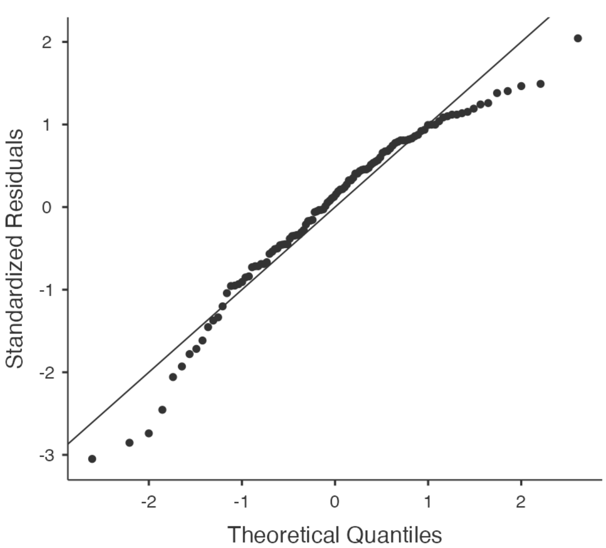
Variable	VIF	Tolerance

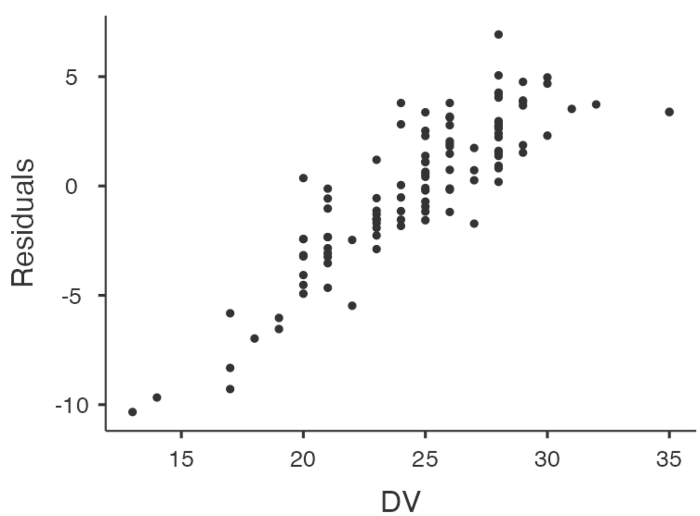
IV1: UI Design Elements	1.47	0.679
IV2: AI Features	1.47	0.679

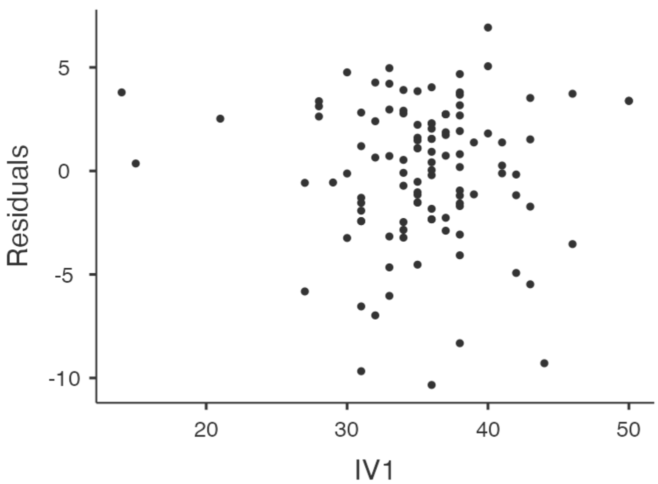
Note: VIF (Variance Inflation Factor) values below 5 and Tolerance values above 0.2 are generally considered to indicate a lack of significant multicollinearity. The results suggest that multicollinearity is not an issue in this model.

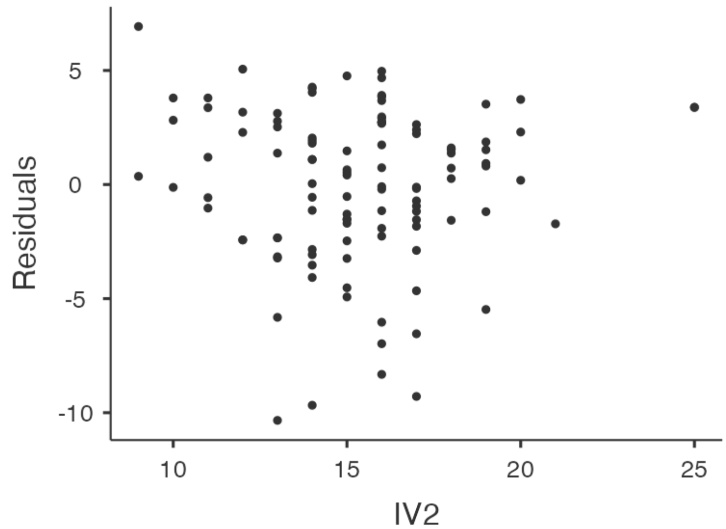
Plots 3:

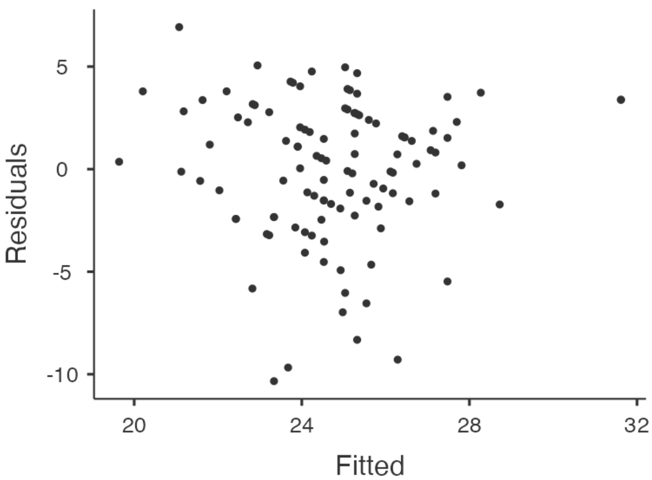
Q-Q Plot & Residual Plot











Further Research

6.1 Practical Implications

The findings of this study provide useful insights for both fintech developers and consumers. For financial institutions, the results highlight the importance of integrating intuitive UI design with transparent and personalised AI features to foster trust and sustained engagement. Specifically, streamlined layouts, consistent visual structures, and gamification elements can enhance usability and satisfaction, while AI-driven personalisation and proactive support functions have the potential to deepen consum er trust and loyalty. Importantly, developers should prioritise AI systems that demonstrate transparency and adopt empathetic, human -like communication styles, as these reduce perceptions of transactional coldness and enhance advisory value.

For consumers, this research clarifies the mechanisms through which design and AI functionalities influence their digital banking experiences. By becoming aware of the role of interface design and transparency, consumers can better evaluate and select banking applications that align with their needs for usability, efficiency, and trust.

These implications are most relevant to digital banking contexts where trust is central to financial decision-making. However, the conclusions may be less transferable to non-financial digital platforms, where risk and user expectations differ significantly.

6.2 Study Limitations

Despite its contributions, this study has several limitations that must be acknowledged. First, reliance on self-reported survey data introduces the possibility of socially desirable responses rather than authentic reflections. Second, the modest sample size of 110 participants restricts the generalisability of the findings across broader or more diverse user populations. Third, the challenge of reducing complex constructs such as “gamification” and “consumer trust” into survey items may have oversimplified participants’ actual experiences and perceptions. These limitations suggest caution in extrapolating findings beyond the immediate sample.

6.3 Recommendations for Further Research

To build upon the insights of this study and address its limitations, several directions for future research are proposed. Future studies could employ experimental designs that systematically manipulate specific UI elements, such as colour schemes or navigation flows, and AI features such as levels of personalisation and transparency, in order to establish causal relationships with trust and engagement. Moving beyond self-reported data, subsequent research should also integrate objective measures such as session duration, feature adoption rates, and interaction frequency to capture real-world engagement patterns more accurately.

Longitudinal studies would provide valuable insights into whether the benefits of well-designed UI and AI features persist, diminish, or evolve with continued usage over time. Similarly, qualitative methods such as interviews or focus groups could uncover the cognitive and emotional factors that shape user trust in AI, shedding light on why certain features are perceived as more reliable or engaging than others. Finally, app-specific investigations into platforms such as Wise or Monzo would allow for a more focused exploration of how UI and AI configurations operate in practice, generating context-specific findings with greater practical relevance.

Chapter 7: Conclusion

7.1 Discusion

The primary aim of this study was to investigate the influence of UI design elements (color palette, information density, and gamification) and AI features (savings recommendations, fraud alerts, and spending categorization) on consumer engagement and trust in AI-powered banking apps. This aim was successfully achieved through a correlational analysis that provided clear and actionable insights.

Based on previous research, it was highlighted that a professional, secure, and aesthetically pleasing interface is a primary driver of initial trust (Casaló, Luis V. ; Flavián, Carlos ; Guinalíu, Miguel , 2024; Chitrakar et al., 2024)). This study extends their findings by demonstrating that these same elements contribute to sustained engagement. Based on the comprehensive study conducted by Liu et al. (2024), it was documented that there were measurable improvements in task completion rates, user satisfaction, and overall engagement metrics when compared to static, non-adaptive interfaces. This indicates that personalised UI Design Elements can effectively increase User Engagement.

These findings align with the results and analysis of this study, which indicated a significant positive correlation ($r= 0.311$, $p < .001$) between UI design elements (IV1) and consumer engagement and trust (DV). The positive correlation found in this study supports the foundational principles of Cognitive Load Theory and Affordance Theory . A well-designed UI, characterised by low information density and intuitive affordances, reduces the cognitive effort required to use the app, thereby making the experience more efficient and enjoyable for consumers. These findings are also consistent with Jakob's Law (Yablonski, 2024), which signifies that users prefer consistency and familiarity. A well-designed UI that aligns with users' mental models from other platforms contributes to a seamless experience, reinforcing engagement and consistency. Thus, the first hypothesis, which states that “Simplified UI designs (low information density, intuitive layouts) positively correlate with higher engagement”, stands accepted.

Based on previous research by Pamisetty (2025), findings suggested that AI plays a dual role in enhancing both security measures and service personalisation within digital banking ecosystems. Other studies conducted by Hari et al. (2021) and

Puneett Bhatnagr and Rajesh (2024) suggest that the utility and intelligence of AI -powered tools like chatbots are significant drivers of user satisfaction and continued use.
These findings align with the results of this study, wherein it was concluded that there is a highly significant positive correlation between AI features (IV2) and consumer engagement and trust (DV), with a strong Spearman's rho of 0.469 and a p-value of <.001. The significantly higher correlation value (0.469) compared to UI design indicates that the tangible benefits provided by AI features, such as savings suggestions, fraud alerts, and effective spending categorisation, act as a stronger and more immediate driver of user engagement and trust. This aligns with the Technology Acceptance Model (TAM), which identifies high Perceived Usefulness as the most influential predictor of user adoption. Thus, the second hypothesis, which states that "AI features that enhance personalisation (e.g., tailored savings tips) increase user engagement", is accepted.

When looking at the combined influence of UI Design Elements and AI Features on Consumer Engagement and Trust, there was a research gap, which was highlighted by Xu et al. (2024), who called for how both the variables can holistically interact with each other and collectively influence Consumer Engagement and Trust. The analysis of this study showed that there is a statistically significant positive relationship between UI design elements and AI features, with a Spearman's rho of 0.416 and a p-value of <.001. The results show that UI and AI are not independent variables in their effect on consumer engagement and trust; rather, they are moderately and positively related. A well-designed, user-friendly, and visually appealing interface acts as the welcoming "front door", makes AI features feel approachable and reliable. In turn, the AI delivers meaningful, valuable functionality that keeps users engaged, proving that the high-quality UI is worth the investment. This connection makes it clear that the best results come from giving equal attention to both intuitive design and powerful, intelligent features. This aligns with the analysis of this study, wherein there was a 25% ($R^2 = 0.250$) prediction towards Consumer Engagement and Trust. This indicates that when AI tool features are present, UI design elements may have little impact on predicting consumer engagement and trust. Signifies that AI features serve as a strong, independent driver of both engagement and trust. Thus, the third hypothesis, which states that "There is a significant positive relationship between UI design elements and AI features in AI-powered banking applications.", is accepted.

In conclusion, this study indicates that both UI design elements and AI features independently contribute to consumer engagement and trust. Analysis revealed a strong positive relationship between AI features (savings recommendations, fraud alerts, and spending categorisation) and User Engagement. This suggests that as the perceived value of these AI functionalities increases, consumer engagement and trust are likely to rise correspondingly. On the other hand, this relationship remains constant even when UI Design Elements are held constant, underscoring the independent predictive capacity of AI features.

Meanwhile, UI Design Elements (colour palette, information density, and gamification) were also significant predictors of Engagement and trust. Thus, a well-designed interface serves as a foundation for user confidence, enhancing usability and overall interaction quality.

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