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Understanding Customer Experience in AI-Based Banking Services: The Role of User Perceptions, Satisfaction and Loyalty

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This dissertation represents much more than the completion of an academic journey. It marks the end of a chapter that, for different reasons, took longer than I had originally expected. Completing it required persistence, the courage to try again and, above all, the determination not to give up on a goal that remained important to me throughout the years.

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Abstract

The banking sector is undergoing rapid transformation driven by the evolution of digital technologies and the increasing integration of Artificial Intelligence (AI) into financial services. Beyond merely automating processes, these technologies are reshaping how customers interact with banks and evaluate the services they use. Despite their growing role in the sector, there remains limited understanding of how user perceptions regarding AI-based banking services influence the customer experience and, subsequently, customer satisfaction and loyalty. Against this backdrop, this study aims to contribute to the literature by proposing an integrated model that analyzes key factors associated with the customer experience in AI-based banking services and their effects on subsequent customer relationship outcomes. The study proposes a model based on the Technology Acceptance Model (TAM) that incorporates perceived trust, perceived risk, perceived security, and perceived privacy, placing customer experience at the core of the analysis. The results indicate that perceived usefulness, perceived ease of use, perceived security, and perceived privacy are positively and significantly related to customer experience, whereas the expected effects of perceived trust and perceived risk were not confirmed. Furthermore, customer experience showed positive relationships with customer satisfaction and loyalty, and a positive relationship was also observed between satisfaction and loyalty. Additional analysis revealed that satisfaction partially mediates the relationship between experience and loyalty. By linking perceptions associated with the use of AI-based banking services to subsequent customer-bank relationship outcomes, this study offers a broader perspective than approaches focused solely on technology acceptance or usage intention. The study also presents relevant practical implications for banking institutions. By understanding the factors that shape the user experience with AI-based banking services, banks can develop more effective strategies to improve these services, boost customer satisfaction, and foster longer-lasting relationships.

Keywords: Artificial Intelligence, Banking Sector, AI-Based Banking Services, Customer Experience, Customer Satisfaction, Customer Loyalty

Resumo

O setor bancário tem vindo a transformar-se rapidamente com a evolução das tecnologias digitais e a crescente integração da Inteligência Artificial (IA) nos serviços financeiros. Mais do que automatizar processos, estas tecnologias estão a alterar a forma como os clientes interagem com os bancos e avaliam os serviços que utilizam. Apesar do seu crescente papel no setor, continua a existir uma compreensão limitada sobre a forma como as perceções dos utilizadores relativamente aos serviços bancários baseados em IA influenciam a sua experiência e, posteriormente, a sua satisfação e lealdade. Neste contexto, este estudo procura contribuir para a literatura através de um modelo integrado que analisa os principais fatores associados à experiência do cliente em serviços bancários baseados em IA e os seus efeitos em resultados posteriores da relação com o cliente. Este estudo propõe um modelo integrado que parte do Technology Acceptance Model (TAM) e incorpora a confiança percebida, o risco percebido, a segurança percebida e a privacidade percebida, colocando a experiência do cliente no centro da análise. Os resultados mostram que a utilidade percebida, a facilidade de utilização percebida, a segurança percebida e a privacidade percebida estão positiva e significativamente relacionadas com a experiência do cliente, enquanto os efeitos esperados da confiança percebida e do risco percebido não foram confirmados. Por sua vez, a experiência do cliente apresentou relações positivas com a satisfação e a lealdade do cliente, verificando-se também uma relação positiva entre satisfação e lealdade. A análise adicional revelou ainda que a satisfação medeia parcialmente a relação entre experiência e lealdade. Ao relacionar percepções associadas à utilização de serviços bancários baseados em IA com resultados posteriores da relação entre cliente e banco, este estudo oferece uma perspetiva mais ampla do que abordagens centradas apenas na aceitação ou intenção de utilização da tecnologia. O estudo apresenta também implicações práticas relevantes para as instituições bancárias. Ao compreender os fatores que moldam a experiência dos utilizadores com serviços bancários baseados em IA, os bancos podem desenvolver estratégias mais eficazes para melhorar estes serviços, reforçar a satisfação dos clientes e promover relações mais duradouras.

Palavras-chave: Inteligência Artificial, Setor Bancário, Serviços Bancários Baseados em IA, Experiência do Cliente, Satisfação do Cliente, Lealdade do Cliente

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1. Introduction

Over the past few decades, the global banking industry has consistently undergone transformative shifts in response to the advancement of technology and the constant evolution of the digital environment. Financial institutions have had to re-think the way they operate to respond to changing behaviors and expectations (Sarkar, 2023), as banking services have become more and more embedded in consumers' daily lives. The increasing connectivity of the customer base, demanding speed, accessibility and efficient service delivery has led to the gradual evolving of traditional banking channels into digital channels that offer financial services at real-time pace (Finextra, 2023). This transformation has also changed the competitive dynamics in the sector. The value propositions of FinTechs are based on technological agility, personalization and innovation, pressuring established financial institutions to innovate (Barroso & Laborda, 2022). Hence, commercial banks have increasingly been challenged to maintain their relevance and profitability in an increasingly digital market (Mehdiabadi et al., 2020). Against this background, AI has gradually entered customer-facing activities, in particular through chatbots and virtual assistants that can answer inquiries, make personalized recommendations and deal with customer complaints (Huang & Rust, 2018). These technologies can offer advantages such as constant availability, more consistent service provision, and lower operational costs (Suraña-Sánchez & Aramendia-Muneta, 2024). However, the increasing presence of AI does not necessarily imply that its potential is fully realized. Organizations might find it difficult to close the disparity between technological capabilities and customer relationship objectives, resulting in a gap between the potential of AI and the actual results achieved during customer interactions (Behera et al., 2024). Moreover, even if AI is taking a more important role in the financial services, the understanding of its implications in this context remains incomplete (Van der Burgt, 2019). Thus, understanding customers' perceptions and experiences of AI-based banking services is especially relevant for banks that wish to meet changing customer expectations and remain competitive in a rapidly changing environment.

Existing research studies on AI in customer-facing financial services have mainly examined the technology performance and consumer adoption behavior, leaving the scope to explore other aspects of the customer perspective (Hentzen et al., 2022). Applications of AI

that involve direct customer interaction in commercial banking have also received relatively little academic attention, although there is potential to change the way banks interact with their customers (Königstorfer & Thalmann, 2020). This gap is also evident in the customer experience literature. The research on the intersection between AI and customer experience is less mature than research focusing on AI and user experience (Peruchini et al., 2024). This highlights a need for further research into factors that shape customers' experiences with AI-based banking services. The present study fills this gap by investigating the relationship between different user perceptions and customer experience and then the relationship between customer experience and customer satisfaction and customer loyalty. This helps to contribute to a wider knowledge of AI-enabled banking than adoption-focused perspectives, as well as offering practical insights for financial institutions aiming to improve client interactions and strengthen customer relationships. The structure of the present dissertation is distributed through six main chapters. After the introduction, a detailed literature review is presented, describing the main concepts and the theoretical basis for the study. Chapter 3 describes the proposed research model and hypotheses, and then the research methodology including the measurement process and data collection. The analysis of the data is presented in Chapter 4 and the main results are presented in Chapter 5. The last chapter contains the conclusions, theoretical and practical implications, main limitations and recommendations for future studies.

2. Literature Review

2.1 Digital Banking and the Transformation of Banking Services

Edelman (2023) associates the transformation of knowledge-intensive sectors such as banking with the growing use of digital technologies, automation, and data-based systems, which have changed how organizations process information, make decisions, and deliver services. These developments have also increased the strategic relevance of digital transformation. Halim et al. (2023) describe it as a priority for organizations seeking greater efficiency, stronger competitiveness, and sustainable performance over time. The same authors understand digital transformation as the integration of digital technologies into organizational activities with the purpose of improving responsiveness, efficiency, and value creation

(Halim et al., 2023). Riedl (2017) stresses that this process goes beyond technological upgrading, since it also involves changes in strategic models and management systems. The capacity to transform digitally depends on several organizational elements working together. Digital transformation can also contribute to organizational performance by improving operational efficiency and productivity (Niu, 2025).

Competitive pressures have given this transformation particular importance in banking. Yu and Liu (2025) report that internet-based technology companies have entered activities traditionally dominated by commercial banks, including payment settlement and microloans, reducing the market share of traditional institutions in some of these areas. Digital transformation has consequently become increasingly relevant within a banking environment where technological firms are competing for activities that were previously concentrated in conventional banks (Yu & Liu, 2025). Hess et al. (2016) also highlight that digital transformation is not only about the adoption of new technologies but also about the transformation of value creation, organizational structures, and strategic priorities. Weill and Woerner (2018) argue that stronger digital client engagement and deeper comprehension of end customers can create opportunities for greater value creation and improved financial performance. Changes are also evident in the way customers use banking services. Martínez de Ibarreta et al. (2025) highlight the role of banking digitalization in the change in consumer behavior and the increasing use of digital banking services. Carlin et al. (2017) show that mobile financial apps can help to access to personal financial information and to help to make better financial decisions. The use of mobile banking has also emerged as an important digital channel for accessing banking services, and its use is influenced by factors such as perceived ease of use and social influence (Malaquias & Hwang, 2019). This move to digital channels has also impacted traditional banking structures. Vives (2019) associates banking digitalization with the need for traditional banks to downsize excess branch capacity and to adjust their distribution models as financial services increasingly shift to digital channels.

Several factors have driven the adoption of digital banking. Among the drivers of e-banking adoption are convenience, lowering costs, changing consumer preferences, technological progress, customer experience, security, and competitive pressure (Martínez de Ibarreta et al., 2025). This trend was further accelerated by the COVID-19 pandemic which increased the demand for digital solutions in financial services (Gavrila Gavrila & de Lucas

Ancillo, 2021; Nagel, 2020). Kitsios et al. (2021) emphasize the growing strategic importance of digital transformation as banks adapt their processes and business models to remain competitive. The emergence of full digital banks is the next stage of this evolution. Traditional banking activities such as account opening, loan approval, and financial consultations were traditionally done through branch-based interactions while digital banks operate through online and mobile channels (Kang & Shin, 2026). Not having a physical branch network can also significantly lower costs, allowing digital banks to provide more attractive interest rates and lower transfer fees than traditional banks (Kang & Shin, 2026). But not all customers have adapted to this transition in the same way. Weber et al. (2024) explain that the decreasing number of physical branches and the increased trend toward digital banking may increase the risk of financial exclusion, particularly for elderly customers. Thus, digital transformation changes not only the internal processes of a bank, but also the conditions of interaction of the client with a financial institution (Martínez de Ibarreta et al., 2025). Furthermore, Maqbuli and Al-Mahmoudi (2026) reveal that digital transformation capabilities, especially digital applications and human resources, can be conducive to organizational performance in the banking sector.

2.2 Artificial Intelligence in Banking

Kaplan and Haenlein (2019) define AI as the ability of a system to flexibly adapt, to perceive external data, to learn from these data, and to use these learnings to achieve specific goals. In banking, AI is already linked to operational and strategic functions. According to Rao et al. (2026), the applications include technologies like machine learning, natural language processing, and robotic process automation in customer service, credit scoring, fraud detection, compliance, and back-office operations. Importance of machine learning in Finance is closely related to the big data that financial institutions have at their disposal (Polireddi, 2024). These systems can be used for extracting valuable insights through the processing of large datasets and can be used for prediction and financial decision making (Polireddi, 2024). Beyond these risk-related functions, AI has important operational applications in banking. AI and machine learning are associated with higher efficiency and accuracy in the banking sector (Mensah et al., 2024). Polireddi (2024) also argues that these technologies can be used to strengthen internal processes, improve cybersecurity, reduce risk and the ability to perform financial processes in a more efficient manner. Machine learning and AI can also help reduce

the time managers spend on routine activities, enabling them to focus more on strategic and critical activities (Polireddi, 2024). Furthermore, the ability to derive insights from customer data can assist in the creation of more informed and personalized financial products and services (Polireddi, 2024).

The introduction of AI into banking, however, involves requirements that go beyond the technology itself. Kalyani and Gupta (2023) identify some of the challenges faced in the implementation of AI in banking including data quality, technological integration, regulatory constraints, availability of skilled human resources, process flexibility and alignment between AI and organizational strategy. Effective integration therefore depends on financial institutions' capacity to meet these technological, organizational and regulatory challenges. Similarly, Svoboda (2023) highlights that banks can gain from AI if they overcome the challenges associated with its implementation. AI-enabled banking experiences can also enhance client engagement at the customer level (Bajaba et al., 2026). The next section moves away from these broader banking applications to the services that provide direct customer interaction with AI-based technologies.

2.2.1 AI-Based Banking Services

The banking digitalization has progressively transformed the way financial services are delivered and experienced by customers. For example, digital-only banks function via virtual channels and mobile apps, thereby minimizing the need for conventional branch interactions (Windasari et al., 2022). Simultaneously, the adoption of FinTech has led to the creation of new banking models, from traditional banks that leverage digital technologies to app-only neobanks (Mogaji, 2023). In this increasingly digital environment, AI has emerged as a significant component of service delivery, particularly in areas where banks engage directly with customers. Applications such as chatbots, personalized services and automated recommendations illustrate how AI is moving beyond internal banking processes, and becoming part of the customer interface (Polireddi, 2024). This development is especially relevant when considering customer relationship management, where the goal is not just to carry out transactions, but to build and maintain relationships with customers over time (Idzikowski et al., 2019). AI enhances the potential of technology-mediated interaction by providing service systems with the ability to react more independently and to adapt based on

information gathered in previous interactions (Wirtz et al., 2018). Within this context, conversational technologies have become increasingly relevant. Huang and Rust (2018) describe the role of AI in service interactions including the use of chatbots to enable communication and more personalized service delivery. Conversational agents in the past have been relatively limited in the types of exchanges they could support, but advances in conversational technologies have gradually increased their ability to support more complex forms of customer interaction (Gnewuch et al., 2017). More recently, generative AI has expanded these possibilities even further, opening new doors for automated customer service and personalized financial assistance in banking (Moharrak & Mogaji, 2025). One of these is personalization, and this is where standard AI can add value to digital banking services. Machine learning and AI can help in developing services and offers that are more in tune with individual customer needs through analyzing customer habits, preferences and behavioral patterns (Polireddi, 2024). Another example of this change toward technology-mediated financial assistance is the robo-advisors that offer automated assistance for financial and investment-related decisions (Belanche et al., 2019). These examples show that AI-powered banking services are no longer limited to automating routine operations but are increasingly shaping the way in which customers receive information, support and financial guidance.

However, the growing use of AI in customer-facing services also raises relational challenges. The quality of these interactions depends not only on whether the technology can complete a task but also on how customers perceive the interaction itself. Chaves and Gerosa (2021) demonstrate that social characteristics embedded in conversational systems can influence how users respond to chatbots. Similarly, Sheehan et al. (2020) found that unresolved communication failures can decrease perceived humanness and users' intentions to adopt customer service chatbots. At the same time, making an automated system more human is not necessarily advantageous. Ciechanowski et al. (2019) found that chatbots that are more human-like may cause more discomfort, which is indicative of an uncanny valley effect. Luo et al. (2019) also found that customers who knew they were dealing with an AI chatbot perceived the agent as less knowledgeable and less empathetic, which negatively impacted their behavioral response. These findings show the insufficiency of the functional assessment of AI-based services alone to assess their effectiveness. A system can solve a problem successfully but still leave the customer with a bad impression of the interaction. Najati (2026) builds on this distinction by introducing the concept of perceived dehumanization, which

describes situations where AI-mediated interactions fail to sufficiently acknowledge the customer's individuality. This perception can be expressed in several ways, such as the author's identification of perceived lack of personalization, emotional attenuation, interactional coldness and digital isolation. The distinction between functional performance and relational experience is especially relevant in the case of banking, where customers are more interacting with automated systems in situations that may involve trust, uncertainty or personal financial issues. Additionally, the role of AI in banking must be understood from the perspective of the ways in which these interactions shape the customer experience, as discussed in the next section.

2.3 Customer Experience in Digital Banking

Customer experience is commonly conceptualized as a multi-dimensional construct, consisting of the diverse ways in which customers respond to their interactions with a firm. According to Gerea et al. (2021), it is cognitive, emotional and behavioral reactions that occur along the customer journey. The perspective is extended by Lemon and Verhoef (2016) with a temporal perspective, stating that customer experience takes place through multiple touchpoints and over time. It is not formed by a single interaction, but by the sum of interactions customers have with an organization along their journey. Likewise, McColl-Kennedy et al. (2019) emphasize the role of individual interactions in the experience that is ultimately constructed by the customer. Customer experience is also relevant in relation to outcomes like satisfaction and loyalty (Mbama & Ezepue, 2018). As customer relationships are more and more mediated by technology, customer experience has also entered digital environments. Kacprzak and Hensel (2023) define online customer experience as the cognitive, emotional and behavioral responses resulting from customer-firm interactions through digital channels. These experiences are accumulated through a sequence of digital interactions, not a single interaction. This change is particularly noticeable in the banking industry, where digital channels are now the core of many customer interactions. Mobile financial services have provided customers to avail banking services on anytime-anywhere basis (Shaikh et al., 2023). It makes customers more independent and less dependent on engagement at a branch. At the same time the higher choice in retail banking makes switching behavior more relevant since price, service quality, reputation and switching costs may affect customers' decisions to switch to a different provider (Clemes et al., 2010). Digitalization has therefore changed the way banking

services are delivered and the way customers experience their relationship with financial institutions.

Customer experience in digital banking is about more than just financial transactions that are successfully completed. Makudza (2021) considers banking experience in terms of virtual, physical and service interactions, illustrating customers' experience of banking in different contexts. Moreover, Susanto et al. (2023) also highlight the psychological aspect of digital banking, such as comfort, anxiety, and pressure in service encounters. This wider perspective is consistent with Mbama et al. (2018) who identified several factors that may shape digital banking experience, for example, service quality, functional quality, perceived value, customization, service speed, staff-client engagement, brand trust, digital banking innovation, perceived usability, and perceived risk. While banking transactions are typically linked to utilitarian goals, functional aspects do not entirely explain the customer experience. Cruz et al. (2010) indicate that affective and flow related factors could also be implicated in the way customers experience banking services. This means customers can not only evaluate if a digital service helps them complete a task, but how it feels to interact with it. The service characteristics may also affect the customer's evaluation of digital banking in different ways. For example, Susanto et al. (2023) have studied usefulness, convenience and security regarding customer satisfaction. The results indicated that convenience and security significantly affect satisfaction, but the hypothesized relationship between usefulness and satisfaction was not supported. It implies that not all dimensions of digital banking are viewed equally by customers. Additionally, digital banking can introduce issues that negatively affect the customer experience. Tiwari et al. (2021) point out that perceived risk and trust are important factors in mobile banking adoption, with security and privacy concerns being part of users' perception on risk. Thus, customer experience in digital banking includes both the benefits of using these services and the concerns or challenges that may arise during the use of these services. As artificial intelligence becomes more prevalent, it adds another layer to these digital experiences. In chatbot banking, Makudza et al. (2024) noted that AI based conversational services can significantly improve the customer experience. Their findings also emphasize the importance of reliability and responsiveness and find a significant association between perceived benefits of chatbot banking and customer experience. As banking services are becoming increasingly automated, it is important to know not only if the technologies perform well, but also how customers perceive and evaluate their interactions with

them. This makes the factors influencing the acceptance and experience of AI-based banking services particularly relevant to investigate.

2.4 Technology Acceptance and Perceptions of AI-Based Banking Services

2.4.1 Technology Acceptance Model

The Technology Acceptance Model (TAM), developed by Davis (1989), provides a theoretical basis for understanding individuals' acceptance of new information technologies. At the center of the model are two perceptions: perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness concerns the extent to which a person believes that using a particular system will improve performance, whereas perceived ease of use refers to the degree to which its use is expected to require little effort (Davis, 1989). These perceptions help explain how users evaluate a technological system and whether they are likely to accept it. A system may offer clear benefits, for example, but still be less appealing when its use is perceived as unnecessarily difficult or demanding. TAM was subsequently extended to incorporate a wider range of influences on technology acceptance. In TAM2, Venkatesh and Davis (2000) introduced social influence and cognitive instrumental processes to explain perceived usefulness and users' intentions more comprehensively. The extension broadened the original model by recognizing that technology acceptance is influenced not only by perceptions of the system itself, but also by the context in which it is used (Venkatesh & Davis, 2000). This broader perspective is particularly relevant in digital banking. Suh and Han (2002) argue that usefulness and ease of use alone may not fully explain customers' acceptance of Internet banking and introduce trust as an additional belief. Their findings show that trust significantly influences Internet banking acceptance, highlighting its role when financial services are accessed through technological channels. Trust has also been examined together with perceived risk. In the context of mobile banking, Luo et al. (2010) show that risk perceptions are especially relevant during the initial stage of technology acceptance. Other studies have extended technology acceptance models to include security and privacy. Merhi et al. (2019), for example, examine perceived security, perceived privacy, and trust as separate constructs in mobile banking. Their results indicate that both security and privacy perceptions influence customers' behavioral intentions towards these services. Such factors are particularly important in financial environments, where technology-mediated interactions often involve sensitive personal and financial information.

The introduction of AI into banking gives renewed relevance to these acceptance-related perceptions. Graham et al. (2025) apply technology acceptance perspectives to banking chatbots and consider usefulness and ease of use among the factors associated with their adoption. Their study also identifies concerns related to security and risk when customers interact with AI-based customer service, particularly because these interactions may involve sensitive financial information. Banking professionals in the study emphasize convenience, availability, and speed as important benefits of chatbots, while placing particular weight on security and trust (Graham et al., 2025). Accordingly, the present study retains perceived usefulness and perceived ease of use from the original TAM as central perceptions in the evaluation of AI-based banking services (Davis, 1989). Trust is included given its relevance to the acceptance of Internet banking (Suh & Han, 2002), while perceived risk reflects concerns identified in mobile banking adoption (Luo et al., 2010). Perceived security and perceived privacy are examined separately, following research that has treated them as distinct perceptions alongside trust (Merhi et al., 2019). Their inclusion is also consistent with more recent research on banking chatbots, where security, risk, and trust continue to emerge as relevant considerations in customer interaction with AI-based services (Graham et al., 2025).

2.5 Customer Satisfaction

Customer satisfaction is usually associated with the degree to which a service satisfies the needs and expectations of users. Oliver (1980) describes satisfaction as a comparison of prior expectations with actual performance. Confirmation or disconfirmation of such expectations will influence the customer's evaluation of the service. In digital banking such expectations are not necessarily stable over time. As technologies evolve and new service features are introduced, customers may re-evaluate their expectations of electronic banking services. Ru-Zhue et al. (2025) show that satisfaction with e-banking services is determined by perceived usefulness, ease of use, perceived value and technological innovation. The authors also point out that attitudes and behaviors of users can change over time, so banks need to constantly adapt their digital offerings to changing customer expectations.

Customer satisfaction and customer experience are two closely related, but not the same things. Customer experience is created through a series of interactions and touchpoints throughout the customer journey and is therefore broader than a single judgment of a service

(Lemon & Verhoef, 2016). Satisfaction may therefore be viewed as an overall judgment that is a consequence of what the customer has experienced rather than the totality of cognitive, emotional and behavioral responses that make up the experience itself. This distinction is especially salient in the domain of digital banking, where customers may have multiple episodes with the same service before they can arrive at an overall evaluation of it. Satisfaction effects go beyond the consumer's evaluation of a banking service as such. Sampaio et al. (2017) investigate the antecedents of customer satisfaction in mobile banking applications, namely trust, loyalty and positive word-of-mouth. Their results emphasize the need for satisfaction to develop a stronger relationship between customers and digital banking services. Recent evidence also links satisfaction to trust. Kim et al. (2026) found that customer satisfaction is a positive predictor of trust in digital banking services, implying that positive experiences can increase customers' confidence in the service provider. Therefore, satisfaction is an important connection between the customers' digital banking experiences and the development of stronger and more lasting customer relationships.

2.6 Customer Loyalty

Customers develop loyalty over time as they feel value in their relationship with a product or service. According to Oliver (1999) loyalty is developed slowly when the purchase and use of an offering is seen as worthwhile. This longer-term perspective is particularly important in digital environments, where initial adoption does not necessarily translate into continued use (Bajwa et al., 2025). Therefore, loyalty and retention are the key to maintaining a stable and committed customer base for internet banking providers in the long run (Dahiya & Singh, 2024).

Loyalty is harder to cultivate in an online banking environment. According to Brun et al. (2014), digital service delivery eliminates the human factor that is normally present in client relationships and, in some instances, eliminates it completely. These conditions have made the drivers of online loyalty an increasingly important business strategy consideration (Toufaily & Pons, 2017). Service quality is one of the factors relating to customer loyalty. Parasuraman and Grewal (2000) suggest a chain where improved service quality leads to improved perceived value and in turn to improved loyalty. This association has also been supported in traditional banking and online banking settings (Jiang et al., 2016). Long and Vy (2016) find a positive association between service quality and customer loyalty in banking.

In the digital environments, service quality is the overall customer judgment about the quality and superiority of services provided through online channels (Amin, 2016). This process is closely related to perceived value. Oliver (1999) found that the probability of loyalty is higher when customers perceive they are getting value from continuing to buy or use a service. In technology-mediated situations, this value may also depend on the characteristics of the interaction itself. Yen and Gwinner (2003) relate customer loyalty to convenience, efficiency, perceived control and technological performance. Thus, continued use may depend not only on access to a service, but also on how well the service is perceived to perform by customers. Trust is also a factor that is connected to loyalty in digital financial services. Ghali (2021) finds a significant association between trust and e-loyalty in electronic banking, with customers mainly engaging with financial institutions through technological interfaces. The strategic value of loyalty becomes particularly clear in competitive digital markets. Yuan et al. (2020) relate it with customer retention and long-term engagement, whereas Ahmed et al. (2023) relate loyalty with business sustainability and competitiveness. Customer loyalty in digital financial services can therefore be conceptualized as the longer-term outcome of the customer-provider relationship.

3. Methodology

This chapter presents the methodological approach adopted to address the research objectives and test the proposed hypotheses. It outlines the research design, data collection procedures, measurement approach, and methods used to analyze the data. In doing so, it establishes the basis for connecting the theoretical framework developed in the previous chapters with the empirical analysis of the study. Given the study's objective of examining customers' perceptions of AI-based banking services and the relationships between these perceptions, customer experience, satisfaction, and loyalty, a quantitative approach was adopted. The constructs in the model can be measured by survey items, which enables the collection of standardized responses from a large sample (Alshammari and Al-Mamary, 2025). Quantitative research is very useful in the measurement of factors and the study of the relation between variables related to attitudes and behavioral responses to technological progress (Draper, 2004). The methodological choices described in this chapter provide a structured basis for the empirical investigation and support the transparency and consistency of the research process. They also establish the procedures through which the proposed

relationships are examined, and the study's findings are subsequently interpreted.

3.1 Research Model and Hypotheses

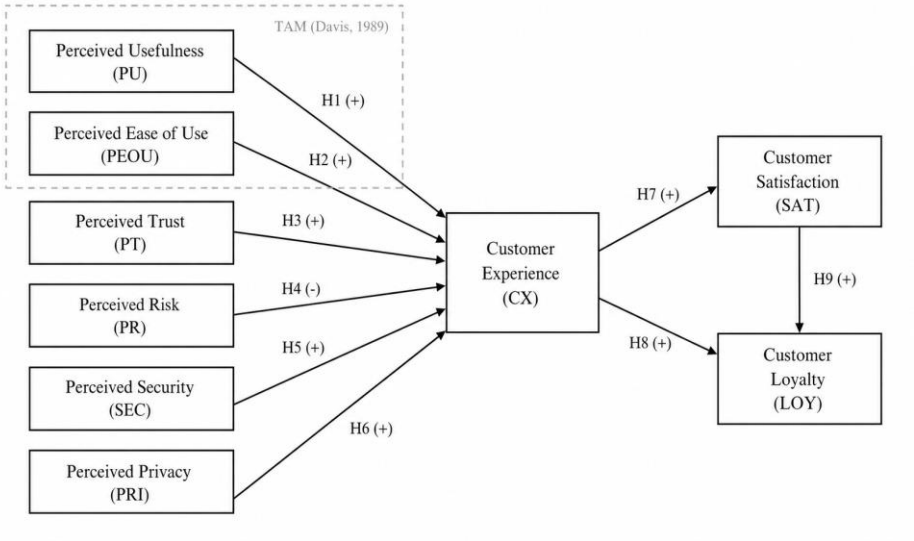
Implementing AI-based banking services, as shown in the last sections, represents a strategic transformation that promotes service quality and efficiency, with the potential to revolutionize fundamental banking functions. The literature review highlighted a limited understanding of the factors influencing customer experience and the relationships between these factors in the use of AI-based banking services. The research model proposed in this study is based on the TAM presented in the previous section. Building on its original constructs, perceived usefulness and perceived ease of use, the model is extended to incorporate perceived trust, perceived risk, perceived security, and perceived privacy. These perceptions are analyzed in relation to customer experience, followed by an examination of the relationships between customer experience, customer satisfaction, and customer loyalty within the context of AI-based banking services. The adoption of the TAM as the theoretical basis of this study is justified by its recognized ability to explain and predict behaviors related to technology acceptance and use. Lee (2009) further highlights that the factors included in the model can support system development by providing relevant guidance during the stages of requirements analysis and development.

Recent research has extended the TAM by including additional perspectives that are specific to technology-mediated banking services. Ikhsan et al. (2025) extended TAM by integrating AI awareness, subjective norms, perceived risk, and perceived trust, contending that these are especially pertinent for customers in the early stages of adoption of the technology. Kaur and Sharma (2022) further extended the TAM to include perceived security and perceived privacy within the framework of e-banking, recognizing the role of these perceptions in customers' use of online banking services.

Finally, while previous studies have incorporated the TAM with factors such as perceived trust, perceived risk, perceived security, and perceived privacy, less attention has been paid to how these perceptions are considered together in relation to customer experience, satisfaction, and loyalty in AI-based banking services. The final model proposed in Figure 1 brings

together the previously discussed factors to provide a broader understanding of customer experience in the use of AI-based banking services. By considering different perceptions associated with these technologies, the model helps identify which factors are more closely related to the way customers experience these services. It also examines how customer experience is connected to customer satisfaction and customer loyalty, offering a broader view of how customers respond to AI-based banking services.

Figure 1: Proposed Research Model



The nine hypotheses tested in this study are presented below, together with the definition of each construct and its relevance within the research context, providing a clearer understanding of the proposed model.

Perceived Usefulness (PU) is one of the core constructs of the TAM and refers to the extent to which a person believes that using a particular system would improve his or her performance (Davis, 1989). In practice, people are more likely to value technologies which will allow them to do their activities more effectively or more efficiently (Davis 1989). This perception is especially important in digital banking, where customers have higher expectations for convenient and efficient services. Perceived usefulness in relation to this study refers to the degree to which users consider AI-based banking services to be helpful and efficient in carrying out their banking activities. Past empirical studies suggest that perceived usefulness is positively related to attitudes toward technology. Users are more likely to adopt a

technology when they see the value of the technology and believe that it can satisfy their needs (Mulyati et al., 2023). When considering AI-based banking services, the perception of clear benefits from the technology may also translate into a more positive customer experience. Hence, the following hypothesis is formulated:

H1: Perceived usefulness has a positive effect on customer experience.

Perceived Ease of Use (PEOU) is another core construct of the TAM and it refers to the degree to which an individual believes that using a particular system requires little effort (Davis, 1989). Simple and easy to understand technologies are perceived as such and require less effort from users and may, therefore, be more readily adopted. This idea is consistent with Rogers and Shoemaker (1971) who associate lower perceived complexity with higher likelihood of technology adoption. Similarly, Venkatesh et al. (2012) connect ease of use to the degree of effort people expect to expend when interacting with a technology. Perceived ease of use for AI-based banking services refers to the degree to which customers perceive that it is easy to understand, use and operate these technologies. Nguyen et al. (2023) emphasize the significance of perceived effort in technology acceptance, showing that the degree of effort perceived to be involved in using a technology can influence consumers' decision-making. It is generally the case that the easier a technology is to understand and use, the more positive the attitude of its users will be (Utomo et al., 2021). Moreover, the perceived simplicity and ease of use of AI-based banking services may also contribute to a better customer experience. Therefore, the following hypothesis is suggested:

H2: Perceived ease of use has a positive effect on customer experience.

Perceived Trust (PT) is an important factor in the acceptance of Internet Banking especially due to the uncertainty associated with online environments. Suh and Han (2002) define trust as "the belief that a service provider will behave in a reliable and responsible manner even when customers have limited control over the transaction". This is especially true for Internet banking, where users are exchanging sensitive financial information and interacting with services that lack the physical cues of face-to-face banking. Trust is also associated with ability, integrity and benevolence perceptions, which are customers' beliefs that the service can operate as expected and act in their best interests (Suh & Han, 2002). Trust is also relevant to technology acceptance more generally. Roca et al. (2009) define perceived trust as the

users' assessment of the reliability and trustworthiness of a technological system, and this can affect the users' willingness to adopt it. Trust has also been linked to users' attitudes and intentions toward technology adoption (Bustaman et al., 2023). Trust is identified as an important factor in the social acceptance of emerging technologies (Wu et al., 2011) and perceived trust can be a facilitator of the continued use of AI-based banking services (Manser Payne et al., 2018). The results suggest that higher confidence in AI-enabled banking services could reduce uncertainty and improve the customer experience. Thus, the following hypothesis has been formulated:

H3: Perceived trust has a positive effect on customer experience.

Perceived Risk (PR) is the uncertainty of the user of the product or service concerning the negative consequences of the use (Featherman & Pavlou, 2003). Risk can be in the form of financial, privacy, social, time and performance related concerns (Lee, 2009). Earlier research has also shown that the prospect of potential losses may inhibit individuals from adopting or using a service (Peter & Ryan, 1976). In digital environments, users may be less willing to disclose information and conduct transactions when the perceived risk is high (Pavlou, 2003). Such concerns could be particularly relevant when AI-based banking services, where customers are dealing with technologies that handle personal and financial data. Hence, perceived risk is the probability that the use of these services may lead to uncertain and undesirable consequences. The higher the perceived potential risk of customers toward AI-based banking services, the more this uncertainty may negatively affect their experience and evaluation of these services. Based on these findings, the following hypothesis is proposed:

H4: Perceived risk has a negative effect on customer experience.

Perceived Security (SEC) refers to the customers' attitude toward the safety of digital banking services, with particular emphasis on financial transactions and sensitive information. The security mechanisms offered by financial institutions can strongly impact the customers' decisions to use technology-based banking services (Chaouali & Souiden, 2019). Positive perceptions of these systems have also been linked to higher use of digital banking channels (Lin et al., 2020) and greater value from the service encounter (Parida et al., 2019). Perceived security within the framework of AI is the perception of users on potential security risks of

their financial information when engaging with AI-based technologies (Manser Payne & O'Brien, 2024). AI-enabled banking platforms can also support the response to security threats by monitoring information, reasoning and acting with some autonomy from human intervention (Srivastava, 2018). Additionally, Manser Payne and O'Brien (2024) identified perceived security as a significant factor influencing customers' intention to use AI virtual agents in basic and advanced banking contexts. Security was the strongest predictor of intention to use AI virtual agents in more complex interactions. The findings support the importance of security perceptions for customer interaction with AI-enabled financial services. This may thus result in a higher perceived security and a more positive customer experience of AI-based banking services. Hence, the following hypothesis is proposed:

H5: Perceived security has a positive effect on customer experience.

Perceived Privacy (PRI) is associated with the degree to which customers believe that their personal information is secured when utilizing online banking services (Ibrahim & Mu'azu, 2021). Privacy concerns are particularly relevant in the setting of AI-enabled financial services, given the highly sensitive personal and financial data involved (Kim & Sung, 2022). Customers are growing more aware of how their data is being used, stored, and shared, and concerns about these practices may lead to reduced trust and engagement with digital platforms (Wahyudi, 2026). Otoo et al. (2025) further note that customers who perceive a higher risk of privacy may respond by withholding information, avoiding the technology, or opting out of it entirely. Privacy related risks may also decrease the level of customer satisfaction and intention to continue using AI-enabled financial services (Kumari, 2026). These findings suggest that concerns about the privacy and use of personal data can affect customers' engagement with AI-powered financial services. Therefore, based on this evidence, greater perceived privacy is expected to contribute to a more positive customer experience when using AI-based banking services. Thus, the following hypothesis has been constructed:

H6: Perceived privacy has a positive effect on customer experience.

Customer Experience (CX), satisfaction, and loyalty represent closely related but distinct outcomes of customers' interactions with banking services. In the proposed model, these constructs are connected through three relationships: customer experience is expected to

influence both customer satisfaction and customer loyalty, while customer satisfaction is also expected to contribute to customer loyalty.

As discussed in the previous sections, customer satisfaction is closely related to the experience that customers obtain from a given service (Lubbe et al., 2025). Positive and memorable experiences have been found to be related to higher levels of customer satisfaction (Raina et al., 2019). Similarly, smooth and seamless interactions can increase satisfaction by reducing the time and effort that customers must dedicate when using a service (Chahal & Dutta, 2014). According to Mbama and Ezepue (2018), if service providers are aware of customers' behavioral patterns and use this knowledge to provide more differentiated experiences, satisfaction can also increase. Hariguna and Ruangkanjanases (2024) state that, when combined with AI, these technologies can support more personalized and responsive customer experiences that may contribute to greater satisfaction. Artificial intelligence can also be used to extract insights from large amounts of customer data (Bowen & Morosan, 2018), allowing services to be more closely adapted to the customers' needs and potentially improving their experience and satisfaction (Prentice et al., 2020). Lubbe et al. (2025) also suggest that seamless, responsive and customer-centered interactions with chatbot-based services can improve consumer satisfaction. These findings together suggest that a better experience using AI-based banking services might lead to higher customer satisfaction.

Customer experience has consistently been associated with the development of customer loyalty. Service positive experiences can increase customers' willingness to maintain the relationship with the provider and recommend their products or services to others (Mulyono & Situmorang, 2018). Empirical evidence also supports this relationship as Srivastava and Kaul (2016) found that customer experience can strengthen attitudinal and behavioral loyalty toward a service provider. Likewise, Klaus and Maklan (2013) reported a strong relationship between customer experience and customer loyalty. Pekovic and Rolland (2020) also emphasize the significance of customer experience in explaining loyalty, suggesting that it may be a stronger predictor of loyalty than customer satisfaction. The findings suggest that positive experience with AI-based banking services can increase customer loyalty. Thus, the following hypotheses have been formulated:

H7: Customer experience positively influences customer satisfaction.

H8: Customer experience positively influences customer loyalty.

Customer Satisfaction (SAT) has been recognized as an important antecedent of customer loyalty (Kamath et al., 2019). Satisfied consumers are also more likely to recommend the products or services of their service providers to others (Mulyono & Situmorang, 2018). The banking sector is also a witness to such relations as Kumar et al. (2010) found that the customer satisfaction has a role in developing attitudinal loyalty among the bank customers. Recent evidence supports this association, as Kim et al. (2024) conclude that customer satisfaction is one of the most commonly reported determinants of customer loyalty in the banking industry. The results indicate that the higher the satisfaction with AI-based banking services, the higher the customer loyalty. Based on the presented arguments, this study proposes the following hypothesis:

H9: Customer satisfaction positively influences customer loyalty.

3.2. Data Collection Approach

The data collection approach adopted in this study consisted of a survey aimed at examining customers' perceptions of AI-based banking services and their relationship with customer experience, satisfaction, and loyalty. This quantitative approach was selected because it allows customers' perceptions and attitudes to be measured in a consistent and comparable way. The use of a survey made it possible to collect standardized responses from participants and subsequently analyze the relationships between the variables included in the research model. Likert-type scales were used to capture respondents' perceptions of AI-based banking services, providing quantitative data suitable for statistical analysis. Given the objectives of this study, the survey was considered an appropriate method for examining how different perceptions of AI-based banking services are associated with customer experience and how this experience relates to customer satisfaction and loyalty. This approach is also widely used in studies addressing research objectives similar to those of the present study, as illustrated in Table 1.

Table 1- Methodological aspects of analogous studies

Paper	Authors	Country	Sample size	Data collection method	Technology
An empirical study on the use of artificial intelligence in the banking sector of Indonesia by extending the TAM model and the moderating effect of perceived trust	Ikhsan et al. (2025)	Indonesia	388	Survey	AI in Banking
Banking on voice: AI attributes, technology perceptions, and trust in banking voicebot acceptance	Liew et al. (2025)	Malaysia	448	Survey	AI Banking Voicebots
The effects of chatbot characteristics and customer experience on satisfaction	Le & Nguyen (2024)	Vietnam	336	Survey	Banking Chatbots
Does artificial intelligence (AI) boost digital banking user satisfaction?	Alnaser et al. (2023)	Pakistan	251	Survey	AI-Enabled Digital Banking
AI-induced privacy concerns: examining the moderating effect of AI fear on customer data sharing	de Matos et al. (2026)	Portugal	408	Survey	AI/E-Banking
Artificial intelligence: understanding the determinants of adoption and intention to recommend the technology in the financial sector in Portugal	Duarte & Baptista (2026)	Portugal	203	Survey	AI in Financial Services

3.3. Survey Implementation

An online questionnaire was developed using Google Forms for the purpose of data collection. Survey instruments are frequently applied in technology acceptance research (Venkatesh et al., 2003), which justified the use of an online questionnaire in the current study. Since the study was primarily disseminated in Portugal, the questionnaire was made available in Portuguese. However, it was initially developed in English, as most of the measurement scales and academic studies used as references were originally published in this language. The questionnaire was subsequently translated into Portuguese by a native speaker and then translated back into English by another individual. Comparing the two versions helped identify possible differences in interpretation and ensure that the original meaning of the items was preserved throughout the translation process. Although the questionnaire was formally available in Portuguese, participation was not restricted by nationality or country of origin. At the beginning of the questionnaire, participants were provided with a brief intro-

duction to AI-based banking services. The purpose was to give respondents sufficient context to understand the scope of the study before answering the questions. The second part of the questionnaire collected sociodemographic information from the respondents, whereas the third part gathered the measurement items used to assess the different constructs included in the research model. Each construct included in the research model was measured using items adapted from previous studies, with between three and five items assigned to each variable. The selection and adaptation of these items aimed to ensure that each construct was appropriately represented within the specific context of AI-based banking services. Before the questionnaire was distributed to the final sample, a pilot test was conducted with five users of banking services. This stage was used to assess the clarity of the questions, the understanding of the terminology, and the overall structure of the questionnaire. Based on the feedback received, minor linguistic adjustments were made before the final data collection began.

3.4. Measures Definition

The measures used in this study were adapted from previously established scales and adjusted to the context of AI-based banking services. Perceived usefulness was measured through four items based on Davis (1989), Pikkarainen et al. (2004), and Marakarkandy et al. (2017). The same sources were used for perceived ease of use, which was also assessed using four items. In both cases, the original wording was adapted to reflect customers' perceptions of AI-based banking services. Perceived trust was measured by four items adapted from Suh and Han (2002) and Kassim and Abdullah (2010) to measure customer perceptions of reliability and trustworthiness of these services. Perceived risk was measured using four items adapted from Featherman and Pavlou (2003) that covered concerns about potential fraud, financial loss, privacy, and unauthorized access when using AI-based banking services. Perceived privacy and perceived security were measured independently. Perceived privacy was measured by four items adapted from Changchit et al. (2023) which addressed the protection, disclosure, and confidentiality of customers' personal and transactional information. Perceived security was measured using five items from the same study which were adapted to study customers' confidence in the security of AI-based banking services and protection of their transactions. Customer experience was measured using four items. Three items were

adapted from Peña-García et al. (2024), and one item was adapted from the previous studies of Roy (2018), Srivastava and Kaul (2016), Sheng and Teo (2012), and Dennis et al. (2014). These items were adapted to evaluate customers' overall experience with AI-based banking services. Customer satisfaction was measured through four items adapted from Kim et al. (2026), addressing customers' satisfaction with the use, available features, transaction-related functions, and overall performance of AI-based banking services. Finally, customer loyalty was assessed using four items. The first two were adapted from Brusch et al. (2019), while the remaining two were based on Mokhtar et al. (2017), covering customers' intentions to continue using and recommend AI-based banking services, as well as positive responses towards their bank. All items were measured using a five-point Likert-type scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"), which is consistent with a common response format in survey research (Taufique et al., 2026). Table 2 summarizes the constructs, number of items, and the sources for these items. The full wording of the adapted measurement items is provided in Appendix A.

Table 2 - Summary of Measurement Constructs and Sources

Construct	Codes	Items	Sources
Perceived Usefulness	PU1–PU4	4	Davis (1989); Pikkarainen et al. (2004); Marakarkandy et al. (2017)
Perceived Ease of Use	PEOU1–PEOU4	4	Davis (1989); Pikkarainen et al. (2004); Marakarkandy et al. (2017)
Perceived Trust	PT1–PT4	4	Suh and Han (2002); Kassim and Abdullah (2010)
Perceived Risk	PR1–PR4	4	Featherman and Pavlou (2003)
Perceived Privacy	PP1–PP4	4	Changchit et al. (2023)
Perceived Security	PS1–PS5	5	Changchit et al. (2023)
Customer Experience	CX1–CX4	4	Peña-García et al. (2024); Roy (2018); Srivastava and Kaul (2016); Sheng and Teo (2012); Dennis et al. (2014)
Customer Satisfaction	SAT1–SAT4	4	Kim et al. (2026)
Customer Loyalty	LOY1–LOY4	4	Brusch et al. (2019); Mokhtar et al. (2017)

3.5. Procedures of Survey Implementation

Data were collected over a period of approximately one month between June and July 2026. The survey was distributed on various digital platforms, including Facebook, Instagram, WhatsApp, LinkedIn and Survey Circle. The questionnaire was shared and reposted several times during the data collection period, especially on Facebook and LinkedIn, by both the researcher and other users to increase its reach and attract a more diverse group of participants. At the same time, individual invitations were sent by WhatsApp and Messenger to contacts of different age groups who met the inclusion criteria of the study. Participants were also asked to circulate the questionnaire to friends, family and acquaintances in their networks, therefore helping to expand the reach of the survey beyond the initial contacts of the researcher. At the end of the data collection period 208 valid responses were received.

3.6. Sample

For this study, the target population consisted of individuals aged 18 or older who use financial services. No restrictions regarding country of residence were imposed, as limiting the sample to a specific geographic location was not deemed necessary for the research objectives. However, a higher representation of residents in Portugal was expected, given that the questionnaire was primarily distributed within that context. The absence of this restriction allowed for the inclusion of participants from diverse backgrounds and captured a range of perspectives regarding the use and perception of banking services. Similarly, no participation criteria were established based on education level, gender, or the frequency of banking service usage. These characteristics, along with age, were recorded to describe the sample composition and explore potential differences between groups. Finally, they served as variables for characterization and supplementary analysis rather than as exclusion criteria for defining the final sample.

4. Data Analysis

Statistical analyzes were performed using IBM SPSS Statistics. This software was used to test the hypotheses developed from the literature review and to conduct the statistical procedures required in this study including reliability analysis, exploratory factor analysis, descriptive statistics, correlation analysis, regression analysis and non-parametric tests. The composite scores for each construct were calculated by averaging the retained measurement items prior to the subsequent analyzes. All hypothesis testing was conducted at the 0.05 significance. Thus, relationships were considered statistically significant when $p < 0.05$, and 95% confidence intervals for the regression coefficients were also reported. The direction and statistical significance of the estimated coefficients were considered in assessing whether each proposed hypothesis was supported. Hayes' PROCESS Model 4 is used in this dissertation (Hayes, 2013). PROCESS is a supplement for SPSS and SAS that facilitates the analysis of mediation, moderation, and conditional process models (Abbu, 2017). Hayes' model is especially helpful for mediation analysis, because it permits researchers to look at indirect effects and to understand how links between variables might work through an intervening variable (Hayes, 2013). The significance of the indirect effect was assessed with bootstrap

confidence intervals based on 5,000 bootstrap samples. The indirect effect was statistically significant if the 95% bootstrap confidence interval (BootLLCI, BootULCI) did not contain zero.

This chapter provides the empirical analysis of the data collected in this study. It starts with the characterization of the sample, and then it evaluates the reliability and measurement structure of the scales. Descriptive statistics and correlation analysis are presented, and the proposed hypotheses are tested by regression analysis. Finally, additional analyzes are conducted to explore the mediating role of Customer Satisfaction and potential differences across demographic groups.

4.1 Sample Characterization

The final sample comprised 208 valid respondents, providing a diverse set of observations across the demographic characteristics considered in this study. Table 3 presents the main characteristics of the participants according to gender, age, education level, and frequency of banking services use. The sample was relatively balanced in terms of gender, with 111 female respondents (53.4%) and 97 male respondents (46.6%). The largest age group was 25-34 years (56.3%) followed by 18-24 years (22.1%). The demographic distribution shows that the majority of the sample are young adults, 78.4% of the participants are between 18 and 34 years old. The rest of the respondents were distributed across the 35-44 (7.7%), 45-54 (7.2%), 55-64 (6.3%) and 65 and over (0.5%) age groups. Regarding education, 44.2% of the respondents had a master's degree and 32.7% a bachelor's degree, while 19.2% had completed secondary education or equivalent. In addition, the educational profile of the sample is characterized by a relatively high level of academic attainment, with 76.9% of respondents reporting either a bachelor's or master's degree. 1.0% of the sample held a doctorate degree and 2.9% selected a different educational level. Finally, the sample was characterized by frequent banking service use. Over half of respondents (55.8%) reported that they used banking services on a daily basis and 36.1% weekly. Monthly and rare users were only 6.7% and 1.4% respectively. In general, 91.9% of respondents used banking services either on a daily or weekly basis. These results provide a clear demographic profile of the study sample and relevant context for interpreting respondents' perceptions of AI-based banking services and the subsequent exploratory analyzes across demographic groups.

Table 3 - Descriptive statistics

Characteristic	Category	N	%
Gender	Male	97	46.6
	Female	111	53.4
Age	18-24	46	22.1
	25-34	117	56.3
	35-44	16	7.7
	45-54	15	7.2
	55-64	13	6.3
	65 or over	1	0.5
Education	Secondary education or equivalent	40	19.2
	Bachelor's degree	68	32.7
	Master's degree	92	44.2
	Doctorate degree	2	1.0
	Other	6	2.9
Frequency of banking services use	Daily	116	55.8
	Weekly	75	36.1
	Monthly	14	6.7
	Rarely	3	1.4

4.2 Scale Reliability and Measurement Assessment

Before moving on to the primary statistical analyzes, this section evaluates the measurement scales' quality. It investigates the underlying factor structure of the measurement items after first looking at internal consistency reliability.

4.2.1 Internal Consistency Reliability

The internal consistency of the measurement scales was confirmed by Cronbach's alpha. According to earlier research, a Cronbach's alpha score of more than 0.7 indicates a high degree of internal consistency (Hair et al., 2017). Cronbach's alpha values were interpreted according to the guidelines proposed by George and Mallery (2003) where coefficients of 0.90 or above indicate excellent internal consistency, values between 0.80 and 0.89 indicate good internal consistency and values between 0.70 and. 0.79 indicate acceptable internal consistency. The overall results demonstrate high reliability coefficients for all constructs, ranging from 0.878 to 0.953. As Table 4 shows, eight of the nine constructs had Cronbach's alpha values greater than 0.90, and the perceived trust also had a good internal consistency with an alpha of 0.878. perceived ease of use presented a Cronbach's alpha of 0.949, while perceived usefulness obtained an alpha of 0.925. Perceived trust had an alpha of 0.878 and perceived Risk reached 0.924. Perceived security ($\alpha = 0.940$) and perceived privacy ($\alpha = 0.953$) also showed high internal consistency. Customer experience and customer satisfaction (pertaining to the outcome constructs) yielded alpha coefficients of 0.949 and 0.946, respectively. The original four-item scale was used to test the Reliability of customer loyalty. Cronbach's alpha was 0.899. However, the item-total correlation for LOY4 was the lowest after correction (0.551). In comparison, the corrected item-total correlations of LOY1 (0.838), LOY2 (0.853), and LOY3 (0.878) were considerably higher, indicating a stronger consistency with the underlying customer loyalty construct. The other loyalty items were much more strongly correlated with the total scale. Removing LOY4 increased Cronbach's alpha from 0.899 to 0.942. In addition to this statistical improvement, LOY4 was related to positive word-of-mouth about the respondent's bank in general, whereas LOY1, LOY2 and LOY3 were specifically related to recommendation, future use and continued use of AI-based banking services. LOY4 was therefore excluded from the final measure of customer loyalty which consisted of three items. On the other hand, reliability analysis showed that if PT3 was removed, the Cronbach's alpha for perceived trust would increase from 0.878 to 0.920. However, the item was not removed because the construct already showed good internal consistency with all four items. It was not considered necessary to remove an item just to obtain a higher reliability coefficient. The final perceived trust measure therefore kept its original four-item structure.

Table 4 - Internal consistency reliability of the constructs

Construct	Items retained	Cronbach's Alpha	Assessment
Perceived Ease of Use (PEOU)	4	0.949	Excellent
Perceived Usefulness (PU)	4	0.925	Excellent
Perceived Trust (PT)	4	0.878	Good
Perceived Risk (PR)	4	0.924	Excellent
Perceived Security (SEC)	5	0.940	Excellent
Perceived Privacy (PRI)	4	0.953	Excellent
Customer Experience (CX)	4	0.949	Excellent
Customer Satisfaction (SAT)	4	0.946	Excellent
Customer Loyalty (LOY)	3	0.942	Excellent

In general, the reliability results provide support for the internal consistency of the measures used in the following analyzes.

4.2.2 Exploratory Factor Analysis

An Exploratory Factor Analysis (EFA) was performed to explore the underlying structure of the measurement items and to examine how the items empirically clustered in the sample. The analysis was performed on the 37 original items using the Principal Axis Factoring technique with Direct Oblimin rotation to allow the extracted factors to correlate. The suitability of the data for factor analysis was determined by using the Kaiser Meyer Olkin (KMO) measure and the Bartlett's Test of Sphericity. The KMO value was 0.943, indicating excellent sampling adequacy for factor analysis. The Bartlett's Test of Sphericity was also significant $\chi^2(666) = 9097.538$, $p < 0.001$, indicating that the correlation matrix was appropriate for factor analysis.

Table 5 - Exploratory factor analysis adequacy measures

Measure	Result
Kaiser–Meyer–Olkin (KMO)	0.943

Bartlett's Test of Sphericity – χ^2	9097.538
Degrees of freedom	666
Significance	< 0.001
Factors initially extracted	5
Cumulative extracted variance	73.067%

The first unrestricted solution yielded 5 factors, accounting for 73.067% of the cumulative extracted variance using the eigenvalue-greater-than-one criterion. Several constructs had a clear empirical structure. Perceived risk was a separate factor, as was perceived ease of use, and perceived usefulness was also relatively consistent in grouping. However, there was substantial overlap amongst some of the theoretically distinct constructs. Customer experience, customer satisfaction and part of customer loyalty tended to cluster together within the same wider factor, while perceived trust, perceived security and perceived privacy also showed significant empirical proximity.

To assess the degree of congruence between the observed structure and the proposed measurement model, an additional EFA was performed specifying a nine-factor solution as the theoretical model separates nine constructs. After increasing the maximum number of iterations, the rotation converged after 35 iterations. The nine-factor solution enabled a clearer distinction of several constructs. The four perceived risk items loaded strongly on the same factor, while the perceived security, perceived ease of use, and perceived usefulness items also showed clear groupings on their respective factors. Perceived privacy also emerged as a separate factor, mainly for PRI2, PRI3 and PRI4. Similarly, LOY1, LOY2 and LOY3 followed a common pattern while LOY4 was inconsistent with other customer loyalty items, providing further empirical support for its exclusion from the final loyalty measure. However, the nine-factor structure was not completely independent. Customer experience and customer satisfaction continued to load mainly on the same factor, indicating a high degree of empirical proximity between these two constructs. There was some overlap within perceived

trust as well with individual trust items having secondary loadings across related factors. However, in the nine-factor solution, PT3 had a communality of 0.531 and a loading of 0.646 on the trust-related factor, giving no strong empirical reason to exclude it.

In conclusion, the EFA supported several dimensions of the proposed measurement structure but also showed that some theoretically distinct constructs were close in the present sample. Therefore, the factor analysis should be regarded as an exploratory assessment of the measurement structure, rather than a confirmation of perfect discriminant separation among all nine constructs. The strong internal consistencies of the scales were also considered in the subsequent analyzes of these results.

4.3 Descriptive Statistics and Correlation Analysis

Descriptive statistics of the nine constructs of the research model are calculated. In Table 6, the mean, standard deviation, minimum, and maximum values for each construct are shown. All constructs were measured on a five-point Likert scale with higher scores indicating stronger agreement with the respective perceptions or evaluations. Perceived usefulness had the highest mean score (M = 3.91, SD = 0.77) among the constructs, suggesting that, on average, respondents were aware of the usefulness of AI-based banking services. Perceived ease of use had a relatively high average score of 3.71 (SD = 0.95). Customer satisfaction (M = 3.60, SD = 0.83) and customer loyalty (M = 3.58, SD = 0.92) also presented means above the midpoint of the scale. Perceived risk had a mean of 3.60 (SD = 0.89), indicating a relatively noticeable level of perceived risk among respondents. Perceived trust (M = 3.48, SD= 0.88) and customer experience (M = 3.48, SD = 0.82) were slightly above the midpoint of the scale. The lowest mean values were also found for perceived security (M = 3.26, SD = 0.87) and perceived privacy (M = 3.26, SD = 0.94), which suggested that these aspects were evaluated relatively more cautiously.

Table 6 - Descriptive statistics

Construct	N	Minimum	Maximum	Mean	SD
Perceived Ease of Use (PEOU)	208	1.00	5.00	3.71	0.95

Perceived Usefulness (PU)	208	1.00	5.00	3.91	0.77
Perceived Trust (PT)	208	1.00	5.00	3.48	0.88
Perceived Risk (PR)	208	1.75	5.00	3.60	0.89
Perceived Security (SEC)	208	1.00	5.00	3.26	0.87
Perceived Privacy (PRI)	208	1.00	5.00	3.26	0.94
Customer Experience (CX)	208	1.00	5.00	3.48	0.82
Customer Satisfaction (SAT)	208	1.00	5.00	3.60	0.83
Customer Loyalty (LOY)	208	1.00	5.00	3.58	0.92

Following that, the bivariate associations among all constructs were examined using Pearson correlation analysis. Table 6 shows that most of the constructs were significantly positively correlated with each other. Perceived ease of use was positively correlated with customer experience ($r = 0.734$, $p < 0.001$). Perceived usefulness was also positively correlated with customer experience ($r = 0.671$, $p < 0.001$).

Perceived trust was positively correlated with customer experience ($r = 0.659$, $p < 0.001$), customer satisfaction ($r = 0.649$, $p < 0.001$) and customer loyalty ($r = 0.705$, $p < 0.001$). Perceived security and perceived privacy also related positively to the main outcome constructs. Perceived security had a correlation with customer experience of $r = 0.708$ ($p < 0.001$) and perceived privacy had a correlation with customer experience of $r = 0.691$ ($p < 0.001$). However, perceived risk was generally negatively related to the other constructs. It was not correlated significantly with customer experience ($r = -0.094$, $p = 0.179$) and customer satisfaction ($r = -0.133$, $p = 0.056$), but it was correlated negatively and significantly with customer loyalty ($r = -0.221$, $p = 0.001$).The highest correlations in the matrix were between customer experience and customer satisfaction ($r = 0.842$, $p <0.001$), then perceived security and perceived privacy ($r = 0.799$, $p <0.001$). Customer experience was also significantly associated with customer loyalty ($r = 0.772$, $p < 0.001$) and customer satisfaction was correlated with customer loyalty at $r = 0.763$ ($p < 0.001$). These relatively high correlations were then considered to assess multicollinearity in the regression models.

Table 7 - Pearson correlation matrix

	PEOU	PU	PT	PR	SEC	PRI	CX	SAT	LOY
PEOU	1								
PU	0.713***	1							
PT	0.660***	0.607***	1						
PR	−0.122	−0.040	−0.354***	1					
SEC	0.587***	0.536***	0.696***	−0.176*	1				
PRI	0.537***	0.487***	0.699***	−0.241***	0.799***	1			
CX	0.734***	0.671***	0.659***	−0.094	0.708***	0.691***	1		
SAT	0.672***	0.707***	0.649***	−0.133	0.662***	0.672***	0.842***	1	
LOY	0.720***	0.640***	0.705***	−0.221**	0.695***	0.712***	0.772***	0.763***	1

*Note. N = 208. Pearson correlations are two-tailed. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

4.4 Regression Analysis and Hypothesis Testing

This section presents the regression analyses used to test the proposed hypotheses. The main regression assumptions and diagnostic indicators were first assessed to ensure the adequacy of the models, followed by the analysis of the relationships proposed in the research model.

4.4.1 Regression Assumptions and Diagnostics

Before testing the proposed hypotheses, the main assumptions underlying the regression analyzes were examined. Diagnostic tests included assessment for residual normality, linearity, homoscedasticity, independence of errors, multicollinearity, and influential observations. For the regression model predicting customer experience from perceived usefulness, perceived ease of use, perceived trust, perceived risk, perceived security and perceived privacy, the residual histogram showed a near normal distribution with some deviation in the lower tail. The normal probability plot also showed an overall acceptable match of observed

and expected residuals. The scatterplot of standardized residuals versus standardized predicted values did not reveal a clear systematic pattern, which supports the assumptions of linearity and homoscedasticity. The Durbin Watson stat for this model was 2.152, which showed no indication of problematic residual autocorrelation. The multicollinearity was also checked with the tolerance and Variance Inflation Factor (VIF) values. The VIF values ranged from 1.221 to 3.249 and the tolerance values were greater than 0.30 for the more highly correlated predictors indicating that multicollinearity did not reach problematic levels. Cook's Distance values were also small, with a maximum value of 0.136, indicating that no single observation exerted undue influence on the regression estimates.

In the model where the relationship between customer experience and customer satisfaction was tested, the distribution of residuals presented some mild departure from perfect normality, but no serious violation was identified. The P-P plot was reasonably in line with the expected diagonal, and the residual scatterplot did not show any clear non-linear pattern or significant heteroscedasticity. Durbin-Watson statistic was 1.976 with a maximum Cook's Distance of 0.072 indicating no problematic influential observations. The regression model to predict customer loyalty from customer experience and customer satisfaction also showed acceptable diagnostic results. Residual plots did not suggest serious departures from normality, linearity, or homoscedasticity. The Durbin-Watson statistic was 1.994, indicating the independence of residuals. The VIF of both predictors was 3.445 and the tolerance was 0.290, which were acceptable and did not show any serious multicollinearity. These comparatively higher values are consistent with the strong correlation observed between customer experience and customer satisfaction ($r = 0.842$), although they did not indicate a level of multicollinearity severe enough to invalidate the regression estimates. The maximum Cook's Distance was 0.073, again suggesting no one case had undue influence on the model.

Table 8 - Regression diagnostic statistics

Model	**Durbin–Watson**	**VIF range**	**Maximum Cook's Distance**
PU, PEOU, PT, PR, SEC, PRI → CX	2.152	1.221 - 3.249	0.136
CX → SAT	1.976	-	0.072

CX, SAT → LOY	1.994	3.445	0.073

To conclude, the diagnostic testing results suggest that the assumptions required for the regression analyzes were reasonably well satisfied, and no serious violations were detected that would impair the interpretation of the subsequent hypothesis tests.

4.4.2 Determinants of Customer Experience

A multiple linear regression analysis was conducted to examine the extent to which PU, PEOU, PT, PR, SEC, and PRI predict customer experience. The whole regression model was statistically significant, $F(6, 201) = 78.802$, $p < 0.001$, with a strong relationship between the set of predictors and customer experience ($R = 0.838$). The model explained 70.2% of the variance in customer experience ($R^2 = 0.702$; adjusted $R^2 = 0.693$) showing a high power of explanation. Perceived usefulness had a positive significant effect on customer experience ($\beta = 0.186$, $t = 3.208$, $p = 0.002$). Hence, H1 was supported. H2 was supported by the significant positive relationship between perceived ease of use and customer experience ($\beta = 0.336$, $t = 5.518$, $p < 0.001$). Customer experience is most strongly standardized by PEOU among the six predictors. Contrary to expectations, perceived trust did not present a statistically significant unique effect on customer experience when the remaining predictors were considered simultaneously ($\beta = 0.031$, $t = 0.460$, $p = 0.646$). Consequently, H3 was not supported. Perceived trust was significantly and strongly positively correlated with customer experience ($r = 0.659$, $p < 0.001$). Perceived trust was also strongly correlated with perceived security and perceived privacy. Thus, its non-significant regression coefficient indicates that Perceived Trust did not account for additional unique variance in customer experience when the other perceptions were taken together at the same time. Similarly, perceived risk did not significantly predict customer experience ($\beta = 0.062$, $t = 1.460$, $p = 0.146$). Although the estimated coefficient was positive rather than negative as hypothesized, the relationship was not statistically significant and should therefore not be interpreted as evidence of a positive effect. Thus, H4 was not supported. Perceived security had a statistically significant positive effect on customer experience ($\beta = 0.193$, $t = 2.776$, $p = 0.006$) which supported H5. Finally, perceived privacy significantly and positively predicted customer experience ($\beta = 0.259$, $t = 3.798$, $p < 0.001$), supporting H6. Based on the standardized coefficients, the strongest significant predictor of customer experience was perceived ease of use ($\beta = 0.336$) followed by

perceived privacy (β = 0.259), perceived security (β = 0.193) and perceived usefulness (β = 0.186). Perceived trust and perceived risk did not contribute statistically significant unique variance to the model.

Table 9 - Multiple regression results for the determinants of Customer Experience

Hypothesis	Relationship	B	SE	β	t	p	95% CI for B	Result
H1	PU → CX	0.198	0.062	0.186	3.208	0.002	[0.076, 0.320]	Supported
H2	PEOU → CX	0.292	0.053	0.336	5.518	< 0.001	[0.188, 0.396]	Supported
H3	PT → CX	0.029	0.063	0.031	0.460	0.646	[−0.095, 0.153]	Not supported
H4	PR → CX	0.058	0.039	0.062	1.460	0.146	[−0.020, 0.136]	Not supported
H5	SEC → CX	0.182	0.065	0.193	2.776	0.006	[0.053, 0.311]	Supported
H6	PRI → CX	0.226	0.059	0.259	3.798	< 0.001	[0.109, 0.343]	Supported

Note: Dependent variable: Customer Experience. $R = 0.838$; $R^2 = 0.702$; adjusted $R^2 = 0.693$; $F(6, 201) = 78.802$, $p < 0.001$

4.4.3 Customer Experience and Customer Satisfaction

H7 proposed a relationship that was tested using a simple linear regression, with customer satisfaction as the dependent variable and customer experience as the independent variable. The model indicated a very strong relationship between the two constructs (R = 0.842) and was statistically significant, F (1, 206) = 503.681, p < 0.001. Customer experience accounted for 71.0% of the variance in customer satisfaction (R2 = 0.710; adjusted R2 = 0.708). This large proportion of explained variance indicates the strength of the relationship between the two constructs. The regression coefficient also confirmed this result. Customer experience had a strong positive effect on customer satisfaction (B = 0.854, SE = 0.038, β = 0.842, t = 22.443, p < 0.001). The corresponding 95% confidence interval was 0.779 to 0.929 and was entirely above zero. These results suggest that higher levels of customer experience

are strongly correlated with higher levels of customer satisfaction. The standardised coefficient also shows that customer experience is a strong predictor of satisfaction in the proposed model.

Table 10 - Regression results for Customer Experience and Customer Satisfaction

Hypothesis	Relationship	B	SE	β	t	p	95% CI for B	Result
H7	CX → SAT	0.854	0.038	0.842	22.443	<0.001	[0.779, 0.929]	Supported

Note: Dependent variable: Customer Satisfaction. $R = 0.842$; $R^2 = 0.710$; *adjusted* $R^2 = 0.708$; $F(1, 206) = 503.681$, $p < 0.001$.

4.4.4 Customer Experience, Customer Satisfaction and Customer Loyalty

The final regression model was on customer loyalty, examining the simultaneous contribution of customer experience and customer satisfaction. At the model level, the two predictors were strongly related to customer loyalty ($R = 0.800$) and the regression was statistically significant, $F(2, 205) = 182.245$, $p < 0.001$. The combined effect of customer experience and customer satisfaction accounted for 64.0% of the variance in customer loyalty ($R^2 = 0.640$; adjusted $R^2 = 0.637$), suggesting that a significant portion of customer loyalty can be explained by these two constructs. When both predictors were entered together, customer experience made a statistically significant positive contribution to customer loyalty ($B = 0.498$, $SE = 0.087$, $\beta = 0.444$, $t = 5.709$, $p < 0.001$). The 95% confidence interval was 0.326 to 0.669. This supports H8.

Customer satisfaction also was a significant positive predictor ($B = 0.430$, $SE = 0.086$, $\beta = 0.389$, $t = 5.006$, $p < 0.001$) with a 95% confidence interval of [0.261,0.600]. Therefore, support was given to H9. The fact that both predictors entered simultaneously suggests that each construct provided unique explanatory information to customer loyalty, although customer experience and satisfaction are strongly associated. Looking at the standardized coefficients, we observe that customer experience had a slightly bigger unique contribution to customer loyalty ($\beta = 0.444$) relative to customer satisfaction ($\beta = 0.389$) while both effects

were significant and substantial. Thus, loyalty seems to be closely related to both the overall customer experience with AI-based banking services and the satisfaction that customers gain from such interactions.

Table 11 - Regression results for Customer Experience, Customer Satisfaction and Customer Loyalty

Hypothesis	Relationship	B	SE	β	t	p	95% CI for B	Result
H8	CX → LOY	0.498	0.087	0.444	5.709	< 0.001	[0.326, 0.669]	Supported
H9	SAT → LOY	0.430	0.086	0.389	5.006	< 0.001	[0.261, 0.600]	Supported

Note: Dependent variable: Customer Loyalty. $R = 0.800$; $R^2 = 0.640$; *adjusted* $R^2 = 0.637$; $F(2, 205) = 182.245$, $p < 0.001$

4.4.5 Summary of Hypotheses Testing

The regression results support seven of the nine hypotheses proposed in the research model. Out of six antecedents of customer experience, perceived usefulness, perceived ease of use, perceived security and perceived privacy had significant positive effects. Perceived trust and perceived risk did not show statistically significant effects when analyzed together with the remaining predictors. Customer experience had positive and significant effect on customer satisfaction and significantly contributed to customer loyalty. Also, customer satisfaction was positively related to customer loyalty, in turn. The results obtained for each hypothesis are summarized in Table 12.

Table 12 - Summary of hypotheses testing

Hypothesis	Proposed relationship	β	p-value	Result
H1	PU → CX (+)	0.186	0.002	Supported

H2	PEOU → CX (+)	0.336	< 0.001	Supported
H3	PT → CX (+)	0.031	0.646	Not supported
H4	PR → CX (−)	0.062	0.146	Not supported
H5	SEC → CX (+)	0.193	0.006	Supported
H6	PRI → CX (+)	0.259	< 0.001	Supported
H7	CX → SAT (+)	0.842	< 0.001	Supported
H8	CX → LOY (+)	0.444	< 0.001	Supported
H9	SAT → LOY (+)	0.389	< 0.001	Supported

Note: β = standardized regression coefficient; (+) = hypothesised positive relationship; (−) = hypothesised negative relationship

These findings confirm most relationships proposed in the conceptual model, but the expected effects of perceived trust and perceived risk on customer experience were not statistically supported.

4.5 Additional Analyses

Beyond the primary hypothesis testing, additional analyses were conducted to examine relationships within the proposed model and potential differences among respondent groups. These analyses included a mediation analysis with customer satisfaction as the mediator and exploratory comparisons by demographic characteristics.

4.5.1 Mediation Analysis

To further investigate the relationship between customer experience and customer

loyalty, we conducted a mediation analysis using Hayes' PROCESS Model 4. The independent variable was customer experience. Customer satisfaction was the mediator, and customer loyalty was the dependent variable. The analysis used 5000 bootstrap samples and a 95% confidence interval. The results showed that customer experience had a significant total effect on customer loyalty (B = 0.8652, SE = 0.0496, t = 17.434, p < 0.001, 95% CI [0.7674, 0.9631]). Customer experience explained 59.6% of the variance in customer loyalty (R2 = 0.596).

The first step of the mediation model also validated a significant association between customer experience and customer satisfaction (B = 0.8543, SE = 0.0381, t = 22.443, p < 0.001, 95% CI [0.7793, 0.9294]). As mentioned earlier in the hypothesis testing, customer experience explained a significant amount of the variance in customer satisfaction (R2 = 0.7097). When customer satisfaction was added to the model, customer experience still had a significant direct effect on customer loyalty (B = 0.4976, SE = 0.0872, t = 5.709, p < 0.001, 95% CI [0.3258, 0.6695]). Additionally, customer satisfaction was significantly associated with customer loyalty (B = 0.4303, SE = 0.0860, t = 5.006, p < 0.001, 95% CI [0.2608, 0.5998]). The indirect effect of customer experience on customer loyalty through customer satisfaction was 0.3676, with a bootstrap standard error of .0808. The corresponding 95% bootstrap confidence interval was 0.2126 to 0.5322. Because the interval did not contain zero, the indirect effect was statistically significant. Importantly, after adding customer satisfaction to the model, the coefficient for customer experience decreased from a total effect of 0.8652 to a direct effect of 0.4976 but remained statistically significant. The results together suggest partial mediation. Thus, customer loyalty relates to customer experience in two ways: directly and indirectly through its link with customer satisfaction. Consequently, increased satisfaction appears to partially mediate the relationship between a positive customer experience and greater loyalty.

Table 13 – Mediation analysis of Customer Satisfaction in the relationship between Customer Experience and Customer Loyalty

Effect	B / Effect	SE / BootSE	95% CI	Significance
Total effect: CX → LOY	0.8652	0.0496	[0.7674, 0.9631]	Significant

Direct effect: CX → LOY	0.4976	0.0872	[0.3258, 0.6695]	Significant
Indirect effect: CX → SAT → LOY	0.3676	0.0808	[0.2126, 0.5322]	Significant

Note: The confidence intervals for the indirect effect were derived from 5,000 bootstrap samples. BootSE = bootstrap standard error.

4.5.2 Exploratory Demographic Analysis

In addition to the main analyses, exploratory tests examined whether respondents' perceptions differed by gender, age, education level, and frequency of use of banking services. These analyses were not included in the initial hypotheses and were therefore treated as supplementary rather than confirmatory. For none of the nine constructs did we observe statistically significant differences across gender groups. Likewise, we found no significant differences by age in PEOU, PU, PT, PR, SEC, PRI, CX, SAT, or LOY. For education level, a statistically significant difference was found only for customer loyalty, $H(4) = 9.599$, $p = 0.048$. However, follow-up pairwise comparisons with Bonferroni adjustment did not identify any statistically significant differences between specific education groups. This result should therefore be interpreted cautiously, particularly because some education categories included very few respondents, such as the Doctorate group.

Frequency of banking service use also showed a statistically significant difference for perceived ease of use, $H(3) = 8.350$, $p = 0.039$. Bonferroni-adjusted pairwise comparisons showed that daily users reported significantly higher perceived ease of use than monthly users (adjusted $p = 0.045$). No other pairwise comparisons were statistically significant, and none of the remaining eight constructs differed significantly according to frequency of use.

Table 14 – Exploratory demographic differences across the study constructs

Demographic characteristic	PEOU	PU	PT	PR	SEC	PRI	CX	SAT	LOY
Gender	0.379	0.518	0.978	0.592	0.285	0.926	0.764	0.619	0.566
Age	0.890	0.162	0.288	0.318	0.635	0.396	0.466	0.098	0.240
Education	0.550	0.564	0.167	0.233	0.096	0.074	0.294	0.632	**0.048**
Frequency of use	**0.039**	0.108	0.087	0.063	0.761	0.788	0.742	0.124	0.555

Note: Values represent p-values from Kruskal–Wallis tests. Bold entries indicate statistically significant results at $p < 0.05$. For Education–LOY, no pairwise comparison remained significant after Bonferroni correction. For Frequency, PEOU, Daily and Monthly users differed significantly after Bonferroni adjustment (adjusted $p = 0.045$).

In conclusion, the exploratory demographic analyses showed little variation in respondent groups. No significant differences emerged for gender or age, and only two omnibus results were significant: customer loyalty across education groups and perceived ease of use across frequency-of-use groups. However, the education result did not survive any significant pairwise comparison after Bonferroni adjustment. The frequency result remained significant between daily and monthly users. These findings should be considered with caution as the analyses were exploratory and some demographic subgroups were small.

5. Discussion

5.1 Discussion of Main Findings

This research aimed to extend understanding of users' perceptions of AI-based banking services by examining how these perceptions influence customer experience and how that experience is reflected in customer satisfaction and loyalty. Therefore, the study not only investigates the determinants of users' experiences with AI-based banking services but also the effect of these experiences on subsequent customer outcomes. To this end, the study used a quantitative methodology involving an online questionnaire as the primary data source, yielding 208 valid responses. We tested the proposed hypotheses, and Table 15 summarises the results.

Table 15 - Results of hypothesis testing

Hypothesis	Proposed relationship	Result
H1	Perceived Usefulness positively influences Customer Experience.	Verified
H2	Perceived Ease of Use positively influences Customer Experience.	Verified

H3	Perceived Trust positively influences Customer Experience.	Not Verified
H4	Perceived Risk negatively influences Customer Experience.	Not Verified
H5	Perceived Security positively influences Customer Experience.	Verified
H6	Perceived Privacy positively influences Customer Experience.	Verified
H7	Customer Experience positively influences Customer Satisfaction.	Verified
H8	Customer Experience positively influences Customer Loyalty.	Verified
H9	Customer Satisfaction positively influences Customer Loyalty.	Verified

The test results supported seven of the nine proposed hypotheses. The analysis revealed that users' perceptions of AI-based banking services are important in shaping customer experience, but not all perceptions contributed in the same way. Perceived usefulness, perceived ease of use, perceived security and perceived privacy had significant positive relationships with customer experience. In contrast, the expected effects of perceived trust and perceived risk were not confirmed. In turn, customer experience was positively related to both customer satisfaction and customer loyalty, and customer satisfaction also positively affected customer loyalty. Additional mediation analysis indicated that customer satisfaction partially mediates the relationship between customer experience and customer loyalty, suggesting that a positive experience can increase loyalty directly and indirectly through higher levels of satisfaction. Most proposed relationships were consistent with previous research, but the non-significant effects of perceived trust and perceived risk contrast with expectations established in the literature.

6. Conclusion

The increasing integration of Artificial Intelligence into banking services is changing not only how financial institutions deliver services but also how customers interact with and evaluate their banks. Against this background, this dissertation sought to advance the understanding of customer experience in AI-based banking services by moving beyond the predominantly adoption-oriented perspective of technology acceptance research. Based on the Technology Acceptance Model (Davis, 1989), the study proposed and empirically tested

an integrated model in which perceived usefulness, perceived ease of use, perceived trust, perceived risk, perceived security, and perceived privacy were analyzed in relation to customer experience, which was then related to customer satisfaction and customer loyalty. The empirical findings provided support for seven of the nine hypothesised relationships. Perceived usefulness, perceived ease of use, perceived security, and perceived privacy were positively and significantly associated with customer experience, whereas the hypothesised relationships between perceived trust and customer experience and between perceived risk and customer experience were not statistically supported when all six antecedents were considered simultaneously. These results suggest that customers' evaluations of AI-based banking services are shaped by a combination of functional and protective considerations. In particular, customers appear to value services that are perceived as useful and easy to use, while also attaching importance to the security of their financial activities and the protection of their personal information. Perceived ease of use was the strongest unique antecedent examined in predicting customer experience. This finding points out the necessity of minimizing effort and complexity in AI-driven banking interactions. Just because a service is technologically sophisticated due to AI doesn't mean customers will have a positive experience unless they can easily understand, access and use the service. At the same time, the substantial links established for perceived security and perceived privacy imply that the quality of AI-based banking experiences cannot be exclusively explained by the conventional functional dimensions of technology acceptance. Since financial and personal data are sensitive, how customers perceive protection appear also to be of importance in the experience of these services. The six antecedents explained a large proportion of the variance of customer experience in total. The regression model accounted for 70.2% of the variance.

However, the non-significance of perceived trust and perceived risk results should not be interpreted as evidence of their irrelevance to AI-based banking. Perceived trust was significantly associated with customer experience but had a high correlation with perceived security and perceived privacy. Thus, its lack of significant unique contribution when predictors were considered simultaneously may suggest that part of the variance associated with trust is shared with these more specific perceptions of security and privacy. Similarly the role of perceived risk may be affected by the technological context, the previous experience of customers and the presence of other perceptions considered simultaneously in the

model. The results emphasize the need to consider technology-related perceptions together, instead of assuming that each one contributes to customer experience independently. A second important conclusion relates to the consequences of customer experience. Customer experience had a significant positive relationship with customer satisfaction, and was also positively associated with customer loyalty. Customer satisfaction was again positively correlated with loyalty. Furthermore, the additional mediation analysis also clarifies these relationships by demonstrating that customer satisfaction partially mediates the relationship between customer experience and customer loyalty. The indirect effect was significant, but the direct effect between customer experience and loyalty was significant even after controlling for customer satisfaction in the model. Customer experience thus seems to be linked to loyalty in two complementary ways: directly, through the overall experience of customers with AI-based banking services, and indirectly, since more positive experiences are associated with greater satisfaction, which is, in turn, associated with greater customer loyalty.

6.1 Theoretical implications

This study provides substantial theoretical contributions and practical implications regarding users' perceptions and experiences with AI-based banking services, advancing both academic understanding and industry practice. Theoretically, the study extends the application of the TAM by examining perceived usefulness and perceived ease of use in the context of customer experience with AI-based banking services. While these two constructs were originally proposed to explain technology acceptance (Davis, 1989), the present study explores their applicability to understanding users' evaluations of their interactions with AI-based banking services. Furthermore, including perceived trust, perceived risk, perceived security, and perceived privacy in the proposed model provides a broader view of the perceptions that may influence customer experience and links these perceptions to subsequent outcomes in terms of customer satisfaction and loyalty.

Moreover, the empirical findings both corroborate and extend previous research. Perceived usefulness and perceived ease of use showed significant positive relationships with customer experience. These results align with Sabir et al. (2023), who found positive and significant effects of both perceived ease of use and perceived usefulness on consumers'

attitudes toward AI-based robo-advisory services, supporting the relevance of TAM constructs in AI-enabled financial contexts. Perceived security and perceived privacy also contributed significantly to customer experience, indicating that evaluating AI-based banking services involves not only functional value and simplicity but also users' perceptions of information protection. Conversely, the expected effects of perceived trust and perceived risk were not supported when all perceptions were considered simultaneously. The non-significant effect of perceived trust contrasts with Payne et al. (2018), who found trust to be a significant predictor of both mobile banking usage and users' comfort with AI banking services. Regarding perceived risk, the non-significant effect found in the present study is consistent with Belanche et al. (2022), who also found no significant direct effect of perceived risk on behavioural intentions in a mobile payment context. However, their findings showed that the effect of perceived risk depended on users' perceptions of security. In contrast, Mbama and Ezepue (2018) identified perceived risk as a factor shaping customer experience in digital banking. These differences suggest that the role of perceived risk may vary by technological context and by the other perceptions considered in the model.

Finally, the study contributes to the literature by linking perceptions of AI-based banking services to more general customer outcomes. Customer experience had strong positive relationships with both customer satisfaction and customer loyalty. Customer satisfaction was positively related to customer loyalty. The results align with previous research in digital banking, which found significant relationships among customer experience, satisfaction, and loyalty (Mbama & Ezepue, 2018). The additional mediation analysis also indicates that customer satisfaction partially mediates the relationship between customer experience and customer loyalty. Thus, positive customer experiences can directly promote loyalty and indirectly enhance loyalty through increased customer satisfaction.

6.2 Practical Implications for Banking Institutions

The results of this study have significant practical implications for banking sector stakeholders. For banks and industry professionals, it is particularly relevant to understand the relationships between the study's constructs and customer experience, satisfaction, and loyalty regarding AI-based banking services. This understanding is fundamental to devising effective and efficient strategies for implementing and enhancing AI-based services within

banking institutions. By understanding the perceptions and factors that shape customer experiences in this context, banking institutions can adapt their features and communication strategies better to meet the needs and preferences of their target audience. Such approaches can improve the effectiveness of AI-based banking services, fostering more positive experiences, higher satisfaction, and stronger customer loyalty.

The results of this research can also help in the development and implementation of AI strategies in the banking industry. In particular, the significant role of perceived ease of use and perceived usefulness suggests that bank management should consider customers' perceptions of simplicity and practical value when designing and improving AI-based banking services. The success of these services thus depends not only on their technological capabilities but also on whether customers perceive them as easy to use and genuinely useful in their banking activities (Sabir et al., 2023). Banks need to ensure that these solutions offer clear value and simplify customer interactions rather than treating AI merely as a technological investment. This might include reducing or removing unnecessary steps, improving how customers find and access AI-based features, and clearly communicating how these services help them complete banking activities more efficiently. AI-based features should also be seamlessly integrated into existing banking processes, rather than requiring customers to adapt to entirely new or complicated ways of interacting with their bank. This can help maintain simplicity and make AI's benefits more visible throughout the customer journey.

Lastly, security and privacy should also be considered important elements in developing AI-based banking services. Both showed significant relationships with customer experience, indicating that customers value not only usefulness and ease of use but also how their personal and financial information is protected. Banks should therefore ensure strong security and privacy practices and communicate them clearly so that customers can understand how their data are used and protected when interacting with AI-based services. Taken together, these findings suggest that banks should approach AI-based services as part of a broader customer experience strategy rather than as isolated technological solutions.

6.3 Limitations and Suggestions for Further Research

This research provides significant insights into the factors influencing customer experience, customer satisfaction and customer loyalty in AI-based banking services. However, several limitations must be considered to support and encourage future research. First, our study participants were mainly younger individuals, who were more likely to adopt new technologies. The demographic bias may affect the generalizability of our results to older groups or to those who are less technologically familiar. Future research should aim to recruit a more diverse sample across a wider age range so the findings can be extended to different population segments.

In addition, using the survey as the primary data collection method may have limited the depth of participants' perceptions and experiences that could be explored and may also have introduced some degree of response bias. Surveys can provide useful quantitative data on the user's experience in large quantities but may not be able to provide the subtleties of the user's opinion and experience. Future research may therefore incorporate qualitative methods (e.g., interviews or focus groups) to complement quantitative methods. They can provide more insight into how users experience AI-based banking services, including motivations, concerns, and contextual factors that survey responses may not fully capture.

Moreover, future research could extend the proposed model by examining other factors that may contribute to customer experience or other outcomes that may result from it. The present study focused on a specific set of user perceptions and on customer satisfaction and customer loyalty. Subsequent studies should explore whether the model remains consistent when other relevant factors or customer outcomes are considered. It would also be useful to examine the proposed relationships across specific types of AI-based banking services, rather than treating these services as a broad category, as this could provide a more detailed understanding of how customer experience forms and develops into subsequent customer responses.

Finally, another limitation is the study's cross-sectional design, as the data were collected at a single point in time. While the findings show relevant relationships between the

constructs, this design does not allow observation of changes in users' perceptions and experiences over time. Future research may therefore use longitudinal approaches to understand how perceptions of AI-based banking services change as users become more familiar with these technologies.

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Appendices

Appendix A: Survey: Constructs' items (English and Portuguese version)

Code	Original item	Adapted item	Sources
PU1	Using an online bank improves my performance of utilizing banking services.	Utilizar serviços bancários baseados em IA melhora o meu desempenho na utilização de serviços bancários.	Davis (1989); Pikkarainen et al. (2004); Marakarkandy et al. (2017)
PU2	Using an online bank enables me to utilize banking services more quickly.	Utilizar serviços bancários baseados em IA permite-me utilizar os serviços bancários mais rapidamente.	Davis (1989); Pikkarainen et al. (2004); Marakarkandy et al. (2017)
PU3	Using an online bank for my banking services increases my productivity.	Utilizar serviços bancários baseados em IA para os meus serviços bancários aumenta a minha produtividade.	Davis (1989); Pikkarainen et al. (2004); Marakarkandy et al. (2017)
PU4	Overall, an online bank is useful for me to utilize banking services.	De modo geral, os serviços bancários baseados em IA são úteis para eu utilizar serviços bancários.	Davis (1989); Pikkarainen et al. (2004); Marakarkandy et al. (2017)
PEOU1	I find it easy to do what I want to do in online bank.	Considero fácil fazer o que quero fazer nos serviços bancários baseados em IA.	Davis (1989); Pikkarainen et al. (2004); Marakarkandy et al. (2017)

PEOU2	Learning to use an online bank is easy for me.	Aprender a utilizar serviços bancários baseados em IA é fácil para mim.	Davis (1989); Pikkarainen et al. (2004); Marakarkandy et al. (2017)
PEOU3	My interaction with an online bank is clear and understandable.	A minha interação com os serviços bancários baseados em IA é clara e compreensível.	Davis (1989); Pikkarainen et al. (2004); Marakarkandy et al. (2017)
PEOU4	Overall, I find an online bank easy to use.	De modo geral, considero os serviços bancários baseados em IA fáceis de utilizar.	Davis (1989); Pikkarainen et al. (2004); Marakarkandy et al. (2017)
PT1	I believe that it is always safe to transfer money using Mobile banking.	Acredito que é sempre seguro transferir dinheiro utilizando serviços bancários baseados em IA.	Suh & Han (2002); Kassim & Abdullah (2010)
PT2	I believe it is reliable to transfer money using Mobile banking.	Acredito que é fiável transferir dinheiro utilizando serviços bancários baseados em IA.	Suh & Han (2002); Kassim & Abdullah (2010)
PT3	My bank promptly informs me whenever anything goes wrong with any of my transactions.	O meu banco informa-me prontamente sempre que algo corre mal com alguma das minhas transações.	Suh & Han (2002); Kassim & Abdullah (2010)
PT4	Based on my past experience, I can say that using Mobile banking is trustworthy.	Com base na minha experiência passada, posso dizer que utilizar serviços bancários baseados em IA é confiável.	Suh & Han (2002); Kassim & Abdullah (2010)
PR1	Using Mobile banking services subjects my banking account to potential fraud.	Utilizar serviços bancários baseados em IA sujeita a minha conta bancária a potenciais fraudes.	Featherman & Pavlou (2003)
PR2	Using Mobile banking services subjects my banking account to financial risk.	Utilizar serviços bancários baseados em IA sujeita a minha conta bancária a risco financeiro.	Featherman & Pavlou (2003)

PR3	I think using Mobile banking services puts my privacy at risk.	Considero que utilizar serviços bancários baseados em IA coloca a minha privacidade em risco.	Featherman & Pavlou (2003)
PR4	Hackers might take control of my bank account if I use Mobile banking services.	Hackers podem assumir o controlo da minha conta bancária se eu utilizar serviços bancários baseados em IA.	Featherman & Pavlou (2003)
PP1	I believe that mobile payment providers will protect the privacy of my personal data.	Acredito que os serviços bancários baseados em IA irão proteger a privacidade dos meus dados pessoais.	Changchit et al. (2023)
PP2	I believe that mobile payment systems will not disclose my personal data.	Acredito que os serviços bancários baseados em IA não irão divulgar os meus dados pessoais.	Changchit et al. (2023)
PP3	I believe that mobile payment systems will keep transactions confidential.	Acredito que os serviços bancários baseados em IA irão manter as transações confidenciais.	Changchit et al. (2023)
PP4	I believe that mobile payment systems will keep my information confidential.	Acredito que os serviços bancários baseados em IA irão manter a minha informação confidencial.	Changchit et al. (2023)
PS1	Using mobile payment enable me to conduct transaction securely.	Utilizar serviços bancários baseados em IA permite-me realizar transações de forma segura.	Changchit et al. (2023)
PS2	I feel confident about the security of mobile payment system.	Sinto-me confiante relativamente à segurança dos serviços bancários baseados em IA.	Changchit et al. (2023)
PS3	I am not worried about the security of mobile payment.	Não estou preocupado/a com a segurança dos serviços bancários baseados em IA.	Changchit et al. (2023)
PS4	I believe that mobile payment systems protect me from unauthorized transactions.	Acredito que os serviços bancários baseados em IA me protegem de transações não autorizadas.	Changchit et al. (2023)

PS5	I believe that the transactions conducted via mobile payment are secured.	Acredito que as transações realizadas através de serviços bancários baseados em IA são seguras.	Changchit et al. (2023)
CX1	I would say that my experience in my bank is excellent.	Diria que a minha experiência com os serviços bancários baseados em IA do meu banco é excelente.	Peña-García et al. (2024)
CX2	I believe I get a higher experience with my bank.	Acredito que obtenho uma melhor experiência com o meu banco através dos serviços bancários baseados em IA.	Peña-García et al. (2024)
CX3	I think the overall experience in the whole process with my bank is excellent.	Considero que a experiência global em todo o processo com o meu banco, através dos serviços bancários baseados em IA, é excelente.	Peña-García et al. (2024)
CX4	My mobile banking needs/requirements are very well met by this mobile bank.	As minhas necessidades bancárias são muito bem satisfeitas pelos serviços bancários baseados em IA.	Roy (2018); Srivastava & Kaul (2016); Sheng & Teo (2012); Dennis et al. (2014)
SAT1	Digital banking services give me an enjoyable utility experience.	Os serviços bancários baseados em IA proporcionam-me uma experiência de utilização agradável.	Kim et al. (2026)
SAT2	I am happy with the variety of service features available in digital banking services.	Estou satisfeito/a com a variedade de funcionalidades disponíveis nos serviços bancários baseados em IA.	Kim et al. (2026)
SAT3	I am happy with the service functions of digital banking services helping settle my transactions effectively.	Estou satisfeito/a com as funcionalidades dos serviços bancários baseados em IA, que ajudam a realizar as minhas transações de forma eficaz.	Kim et al. (2026)

SAT4	I am impressed with the overall performance of digital banking services.	Estou impressionado/a com o desempenho geral dos serviços bancários baseados em IA.	Kim et al. (2026)
LOY1	I will recommend the online shop to my friends.	Irei recomendar os serviços bancários baseados em IA aos meus amigos.	Brusch et al. (2019)
LOY2	I intend to visit the online shop in the future.	Pretendo utilizar serviços bancários baseados em IA no futuro.	Brusch et al. (2019)
LOY3	I intend to continue using mobile banking application X for my banking needs.	Pretendo continuar a utilizar serviços bancários baseados em IA para as minhas necessidades bancárias.	Mokhtar et al. (2018)
LOY4	I often say positive things about my bank to others.	Costumo dizer coisas positivas sobre o meu banco a outras pessoas.	Mokhtar et al. (2018)

Appendix B: PROCESS Model 4 Output in SPSS

***************** PROCESS Procedure for SPSS Version 5.0 *****************

Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****
Model: 4
Y: LOY_MEAN
X: CX_MEAN
M: SAT_MEAN

Sample
Size: 208

****

OUTCOME VARIABLE:
SAT_MEAN

Model Summary

R	R-sq	MSE	F	df1	df2	p
,8425	,7097	,2027	503,6813	1,0000	206,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	,6218	,1363	4,5632	,0000	,3531	,8904
CX_MEAN	,8543	,0381	22,4428	,0000	,7793	,9294

****

OUTCOME VARIABLE:
LOY_MEAN

Model Summary

R	R-sq	MSE	F	df1	df2	p
,8000	,6400	,3085	182,2452	2,0000	205,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	,2929	,1764	1,6604	,0984	-,0549	,6407
CX_MEAN	,4976	,0872	5,7086	,0000	,3258	,6695
SAT_MEAN	,4303	,0860	5,0062	,0000	,2608	,5998

********** DIRECT AND INDIRECT EFFECTS OF X ON Y **********

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
,4976	,0872	5,7086	,0000	,3258	,6695

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
SAT_MEAN	,3676	,0803	,2162	,5283

********** ANALYSIS NOTES AND ERRORS **********

Level of confidence for all confidence intervals in output:
95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
5000

------ END MATRIX -----