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Role of Customer Loyalty in online banking services through Artificial Intelligence (AI)

Sohaib Uz Zaman[1], Mazhar Ahmed Ansari[2], Syed Hasnain Alam[3], Rana Faisal Iqbal[4]

[1]Assistant Professor, Karachi University Business School, University of Karachi, ORCID: https://orcid.org/0000-0002-0135-3292, sohaibuzzaman@uok.edu.pk
[2]Karachi University Business School, University of Karachi, mazharahmed914@gmail.com
[3]Karachi University Business School, University of Karachi, ORCID: https://orcid.org/0000-0002-5008-7365, hasnainalam@gmail.com
[4]Deputy Director, Academics, Ilma University, rfaisaliqb@gmail.com

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Abstract
Artificial Intelligence (AI) has completely changed how customers interact with banks thanks to its integration into electronics consumer relationship management (E-CRM) systems. The impact of artificial intelligence (AI) on client loyalty in Pakistan's banking sector is examined in this study, using Karachi. Perceived usefulness (PU), perceived ease of use (PEU), and intent to adopt AI (IAI) are examined in relation to the efficacy of E-CRM and customer loyalty, using the Theory of Acceptance Model (TAM) as a conceptual framework. Standardized surveys were used to collect information regarding 300 participants in a quantitative research manner. According to statistical study using Partial Least Squares Structural Equation Modeling (PLS-SEM), the integration of AI has a minor effect on customer loyalty, although PEU and PU both greatly enhance the adoption of E-CRM. Despite being geographically particular, the study's conclusions have wider ramifications and serve as a foundation for further research on how AI affects customer engagement tactics across a range of sectors.

Keywords: **Perceived Ease of Use, Perceived Usefulness, ECRM, Intention to Adopt AI and Customer Loyalty**

Introduction
Customer Relationship Management (CRM) has become a crucial strategy for organizations aiming to improve their competitiveness and cultivate customer loyalty. By efficiently managing customer interactions, businesses can boost sales growth and enhance customer satisfaction (Bhalerao et al., 2022). CRM systems allow organizations to optimize processes and leverage customer data to guide strategic decision-making (Kumar et al., 2023). As technology rapidly advances, traditional approaches to managing customer relationships have undergone significant transformation, highlighting the need for a robust system capable of managing complex data analytics and customer interactions.

The incorporation of advanced technologies, especially Artificial Intelligence (AI), has transformed CRM systems significantly. AI can process extensive data sets, revealing insights that are often beyond human analytical capabilities (Chatterjee et al., 2020). This functionality enhances operational efficiency and enables personalized customer interactions, contributing to higher retention rates. AI-powered CRM platforms employ machine learning algorithms to discern patterns in customer behavior, empowering businesses to predict future needs and customize their offerings accordingly (Angraini, 2022). The growing dependence on data-driven strategies underscores the critical role of intelligent systems in contemporary CRM practices.

However, the successful integration of AI in CRM faces considerable challenges, such as data privacy concerns and the need for technological adaptability within organizations (Majumdar & Chattopadhyay, 2020). With strict regulations like GDPR and diverse compliance requirements worldwide, businesses must prioritize customer data protection (Zhou et al., 2021). Addressing these challenges requires a strategic approach to AI adoption, highlighting the necessity for clear policies and frameworks regarding customer data use. Without a solid strategy, organizations may encounter legal issues and jeopardize customer trust.

The primary objective of CRM is to develop strong customer relationships, directly influencing profitability and market positioning (Munandar et al., 2022). Organizations are not solely concentrating on customer acquisition; they are also heavily investing in retaining existing customers through ongoing engagement and service enhancements (Rahman et al., 2022). This shift emphasizes crafting personalized experiences that align with customers' preferences, thereby building loyalty and promoting repeat business.

AI-driven CRM systems demonstrate significant potential in predicting customer behavior and preferences, facilitating proactive service delivery (Kumar et al., 2024). By utilizing AI technology, organizations can automate routine tasks, enabling human representatives to concentrate on complex queries and provide personalized assistance (Roseline et al., 2022). As customer interaction volumes rise, leveraging AI becomes critical for organizations aiming to sustain their competitive advantage and meet evolving customer demands. In this scenario, emphasis should be placed not only on technological advancements but also on the human elements of customer interaction.

Ultimately, the adoption of AI-enhanced CRM strategies enables organizations to prioritize customer-centric approaches, resulting in better customer experiences and increased loyalty. This study aims to investigate the implications of AI integration within CRM systems and its impacts on customer behavior in the Pakistani banking sector (Al-Araj et al., 2022). By examining how banks utilize AI technologies for customer engagement, this research seeks to offer valuable insights into the effectiveness of these strategies in improving customer satisfaction.

Introduction to Industry

The banking sector has experienced significant transformation as a result of technological innovations. Artificial Intelligence (AI) is crucial in redefining banking operations by enabling real-time data analysis and improving decision-making processes (Kumar et al., 2021). Financial institutions are progressively allocating investments towards AI technologies to automate procedures, optimize customer service, and bolster risk management (Vasarhelyi et al., 2020). This evolution has culminated in a more efficient and customer-centric banking experience that aligns with the requirements of the digital era.

Worldwide, the financial services sector is expected to create substantial value through AI, with projections indicating an additional USD 1 trillion annually for banks by 2030 (Consultants et al., 2022). This growth is linked to the enhanced efficiency that AI brings in managing customer interactions and automating processes (Amer et al., 2021). These improvements go beyond operational efficiencies, encompassing product development, enhancements in customer service, and capabilities in risk assessment. Banks utilizing AI-driven analytics can gain deeper insights into market trends and customer preferences, allowing them to provide customized financial solutions.

In Pakistan, the banking sector's embrace of AI technologies has been essential for enhancing customer service and operational efficiencies. The industry has undergone a technological transformation, moving from traditional banking practices to automated systems that improve customer experiences, such as chatbots and personalized banking applications (Nazareno et al., 2021). As consumer expectations change, banks in Pakistan are increasingly committed to providing timely and relevant services that anticipate customers' needs, ultimately boosting overall satisfaction.

The integration of AI technologies in banking promotes advanced data analytics, allowing banks to gain deeper insights into customer behaviors and preferences (Daud et al., 2021). AI-driven predictive analytics can anticipate demand fluctuations for specific banking products and services, enabling institutions to adjust their offerings accordingly. Additionally, AI applications like sentiment analysis assist banks in assessing customer satisfaction levels in real time, allowing them to respond to concerns swiftly and effectively.

As the demand for efficient financial services rises, banks in Pakistan are making substantial investments in AI-driven solutions. This transition improves service delivery and enhances customer satisfaction and loyalty, critical for sustained growth in the financial sector (Ullah et al., 2022). The emphasis on digital banking solutions has intensified due to the COVID-19 pandemic, which compelled banks to innovate swiftly in response to shifting consumer behaviors and preferences.

Problem Statement

Despite the potential advantages of AI in the banking sector, significant challenges persist, particularly concerning data privacy and security (Kumar et al., 2023). As banks increasingly depend on AI technologies, it is essential to address these issues to preserve customer trust and confidence. Protecting customer data from breaches and unauthorized access is critical, as any failure can have catastrophic implications for both banks and their clients. Additionally, successfully implementing AI necessitates substantial investments in technology infrastructure and employee training (Murinde et al., 2022). Banks must navigate these challenges while seizing the opportunities AI offers for improving customer interactions. Training programs are vital to equip staff with the skills needed to effectively utilize AI tools, ensuring a seamless transition to more automated processes.

This study aims to explore how the integration of AI in CRM systems can tackle existing challenges while maximizing customer satisfaction and loyalty. Utilizing the Theory of Planned Behavior (TPB), the research will assess the factors influencing customer adoption of AI in banking services, such as perceived usefulness, ease of use, and user trust. Understanding these factors is crucial for comprehending how customers perceive and engage with AI-enhanced services.

The incorporation of AI within CRM systems holds transformative potential for the banking sector in Pakistan. By prioritizing customer-centric strategies and addressing present challenges, banks can improve their service offerings, ultimately fostering customer loyalty and promoting sustainable profitability. As financial institutions persist in adapting to the digital landscape, the significance of AI in transforming customer relationship management will increase, underscoring the need for banks to strategically invest in and implement AI technologies. Future research should extend to examining the implications of AI in CRM beyond the banking sector. Comparative studies across various industries could reveal common practices and challenges, offering a broader perspective on customer relationship strategies in an increasingly digital environment. As AI technology continues to evolve, its effects on customer engagement, service delivery, and overall business performance will be a key focus area for both academics and practitioners. This exploration will be vital in understanding how AI can enhance not only customer relationships but also operational efficiency within diverse sectors.

Research Objective

This study aims to examine the factors influencing electronic customer relationship management (ECRM) practices and their correlation with customer loyalty in the banking sector. Additionally, it seeks to determine the impact of the intention to adopt AI technologies within CRM systems, analyzing how AI adoption influences customer perceptions, engagement, and overall loyalty in banking services. By exploring these aspects, the research will provide insights into the effectiveness of ECRM strategies and the role of AI in enhancing customer relationships and sustaining loyalty in the banking industry.

Significance of the Study

The significance of this research is in its analysis of how artificial intelligence (AI) affects client loyalty in the banking industry, specifically using the framework of electronic customer relationship management (E-CRM) apps. Regulators or executives from banks may benefit greatly from this research's identification of the factors that influence consumer loyalty and the readiness to embrace AI technology. According to the results, businesses may improve customer happiness and loyalty by honing their marketing tactics, building consumer trust, and improving service delivery. The empirical data on the connections between perceived benefit, perceived simplicity of use, and loyalty from consumers is another way that this study adds to the body of knowledge already available on AI and E-CRM. This information will help guide future investigations and real-world applications in the banking sector.

Scope of the Study

The investigation primarily examines the banking industry in Karachi, Pakistan, with a particular focus on the influence of intelligent technology integration on client loyalty in digital customer relationship management (E-CRM) systems. In order to get information from a representative sample of banking customers, this study uses a quantitative technique and questionnaires. It looks at how several factors, such perceived utility, ease of use, and intention to employ AI technology, relate to one another. Because of its cross-sectional data collection and unique geographic focus, the study acknowledges limitations in extrapolating the results to other areas or nations, even though the findings provide insightful information relevant to the local environment. Future research is advised to examine these dynamics in diverse contexts with larger sample sizes to further enhance the understanding of AI adoption within the global banking sector.

This chapter starts with the background of our topic and then addresses the problem. Now define the aim of our research and then determine some research questions of the variables. Furthermore, more elaborate the limitations of our study follow, and which things mainly focused on in this research. Our findings clarified that all the factors of ECRM are essential to their customer experience and lead towards their loyalty.

Theoretical Background

Technology Acceptance Model (TAM)

Davis' (1986) Technology Acceptance Model (TAM) stands as a popular framework to examine user reactions to technology-based systems. TAM asserts Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) comprise the fundamental elements that shape individual technology adoption decisions. PEOU describes the measure to which an individual expects particular systems to minimize effort yet PU represents system-driven performance enhancement according to Davis (1989). TAM uses TRA as its foundation to explain how people adopt technology across different situations. The findings of Venkatesh and Bala (2008) incorporated experience-based and user attitude variables into TAM which added credibility to its practical application for technology adoption research.

TAM to present a robust theoretical structure which establishes how Perceived Ease of Use connects to Perceived Usefulness while affecting the intention to adopt AI intelligence. The developed model structurally corresponds to TAM constructs since PEOU directly affects PU which leads consumers toward adoption intentions. E-CRM dimensions including security with problem-solving along with customer orientation and technology serve as external elements that influence user assessments of AI systems' usefulness. Gefen et al. (2003) demonstrated that users base their assessment of system utility on security and trust factors before forming their intention. Venkatesh and Davis (2000) showed how perceived ease of use both directly influences adoption intention while simultaneously increasing perceived usefulness according to your model. AI-powered E-CRM solutions influence Customer Loyalty because TAM shows that continued usage and favorable assessments create this outcome.

Literature Review

Chatterjee et al. (2020) highlight that Artificial Intelligence (AI) integrated Customer Relationship Management (CRM) systems can enhance firm value by identifying and retaining top customers. The effectiveness of these advanced technologies largely depends on employee adoption. However, there is limited research focused on examining employees' acceptance of AI integrated CRM systems. To address this gap, this study proposes a conceptual model to predict employees' behavioral intent to use AI integrated CRM systems in organizations. Utilizing the meta-UTAUT model as a theoretical framework, the study extends it by adding constructs such as compatibility, CRM quality, and CRM satisfaction relevant to the organizational context. Future researchers are encouraged to empirically test the proposed model using data collected from employees who utilize AI integrated CRM systems.

Paju et al. (2020) discuss the significant advancements in Artificial Intelligence (AI) technologies in recent years. Previously, utilizing these technologies required substantial internal capabilities to develop machine learning algorithms and implement them within applications such as social media platforms and virtual assistants. Now, the potential for integrating these innovative technologies into enterprise systems (ES) has gained attention from numerous companies. Among the various categories of enterprise systems, Customer Relationship Management (CRM) systems play a crucial role, as businesses across diverse industries increasingly strive to adopt a more customer-centric approach. Various CRM system providers, including Salesforce and Oracle, are increasingly offering AI-CRM applications to enhance the business operations of their customer companies. Despite the growing interest in these applications, companies have limited experience with them, and there are few roadmaps available for guidance. This thesis aims to provide organizations planning to implement AI-CRM applications with a tool to analyze the necessary prerequisites for successful adoption. The fit-viability model (FVM), which has been previously applied to evaluate different IT initiatives, will be further developed and tested in the context of AI-CRM applications. The study consists of two parts. The first part involves background research that focuses on gathering insights from experts regarding the implementation of AI-CRM applications and identifying various applications available in the market through Internet research.

Faramania et al. (2021) explored how technological advancements have transformed consumer behavior across Indonesia, serving as a foundation for the rise of e-commerce—a digital business model increasingly utilized for purchases via applications or websites. Consequently, it is essential for an e-commerce platform to foster e-loyalty to distinguish itself among numerous competitors. This study represents the inaugural investigation into ten factors that impact the value of e-Customer Relationship Management (e-CRM) on e-loyalty in Indonesia. The research surveyed 767 active users of the leading e-commerce company in the country. An empirical analysis was conducted to validate the measurement items related to e-CRM factors and e-loyalty indicators, employing Explanatory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The analysis utilized Structural Equation Modeling (SEM) for hypothesis testing. The findings indicated that the variables of customization, care, cultivation, choice.

Mokha et al. (2021) examined the disruptions in business operations caused by the COVID-19 pandemic. In response, the government has effectively prioritized the health and safety of its citizens and businesses. The banking industry is now tasked with delivering seamless services to meet the urgent needs of customers. The pandemic has notably altered customer attitudes, behaviors, and purchasing habits, changes anticipated to persist beyond the pandemic. These adaptations can be leveraged through the efficient and effective implementation of E-CRM tools, which aim to address customer needs. This study sought to analyze the role of E-CRM in navigating the COVID-19 crisis from both banking and customer perspectives. It also aimed to identify key challenges currently faced by the banking industry and develop concrete strategies to address these issues. The research involved 750 bank customers selected through convenience sampling. Data were analyzed using descriptive.

Alshurideh et al. (2022) investigate the objective of the study, which is to evaluate the influence of electronic customer relationship management (e-CRM) on the quality of service in private hospitals within Jordan. The study delineates the dimensions of customer relationship management (CRM) as website design, website search functionality, privacy, security, and timely service delivery, while the dimensions of service quality are characterized by reliability, responsiveness, assurance, and empathy. The research is specifically concentrated on private hospitals in Jordan. Data collection was primarily conducted through self-reported questionnaires designed using Google Forms, which were distributed to a purposive sample of inpatients via email. The statistical software AMOS v24 was employed to test the hypotheses posed in the study. Findings indicated that electronic customer relationship management significantly enhances service quality. In light of these findings, the researchers recommend enhancing the practice of electronic customer relationship management by reassessing the design and functionality of hospital websites.

Almajali et al. (2022) conducted a study focusing on individuals with online shopping experience, particularly regular customers of Carrefour in Jordan. Data were collected through the distribution of 550 questionnaires, with the assistance of four trained and certified research aides. Analysis was performed on the 320 returned questionnaires using Structural Equation Modeling (SEM). The study examined several factors influencing the effectiveness of electronic customer relationship management (E-CRM) systems, including system quality, information access, security, training, and customer satisfaction. Findings revealed that security, system quality, training, and access to information positively influenced user satisfaction, which in turn impacted the effectiveness of E-CRM. However, it was noted that the relationship between training and E-CRM effectiveness in online shopping was not mediated by user satisfaction.

Al-Bashayreh et al. (2022) conducted an evaluation of the relationships among variables pertinent to the success of electronic customer relationship management (e-CRM). The primary aim of this research was to investigate the impact of various factors, including technological readiness, privacy concerns, the influence of COVID-19, customer pressure, trust, service quality levels, and customer satisfaction. Employing quantitative research methodologies, the study analyzed causal relationships among the key variables. A purposive sampling approach was utilized, leading to data collection from 390 completed questionnaires filled out by employees involved in CRM technology initiatives within Jordanian firms. The analysis was conducted using AMOS software version 22, with hypotheses assessed through structural equation modeling (SEM). Results from the study indicated that technological readiness, COVID-19, customer pressure, and customer satisfaction positively affected the success of e-CRM systems. Furthermore, it was found that technological readiness, privacy, and service quality levels contributed positively to customer satisfaction. The research also demonstrated that customer satisfaction mediated the relationship between trust and e-CRM system success, as well as the relationship between service quality and e-CRM success. Practical implications of this study suggest that managers and practitioners can use these insights to effectively implement e-CRM systems. Additionally, the findings could stimulate further empirical research on the relationships among technological readiness, privacy, COVID-19, customer pressure, trust, service quality, and customer satisfaction. Notably, few studies have addressed these variables in the context of e-CRM success, especially in emerging industries of developing countries, highlighting the need for more exploration in this area.

Hypothesis Development

Perceived Ease of Use and Perceived Usefulness

The extent of how consumers have no experience with complication when acquiring, comprehending, and using a new technology is known as perceived ease of use, or PEU. It has to do with the idea of using technology with little effort (Davis, 1989). Additionally, studies indicate that PEU may directly impact PU (Davis et al., 1989; Chen et al., 2001). The results of Ramayah et al. (2005) show that PEU can mediate through users' attitudes to affect their intents. The assessment of a certain activity as either positive or negative is represented by attitude beliefs (Ajzen and Fishbein, 2005). When people enjoy the entire process, the concept of ease of use is strengthened (Van van Heijden, 2003). Since it includes aspects of interest & satisfaction in using a system, this concept is linked to users' views of Hedonic Feeling in Action (HEA) (de Graaf et al., 2019).

The degree to which people think that using a specific tool or system might improve their productivity at work is known as perceived usefulness, or PU (Davis, 1993; Seddon, 1997; Al-Gahtani, 2001). According to research, PU either directly or indirectly affects users' behavioral intentions to embrace a new system (Agarwal & Karahanna, 2000). Additionally, a number of studies have shown that PU directly influences users' inclinations to interact with the system (Szajna, 1996; Wu and Wang, 2005). Furthermore, PU might indirectly affect intention by way of intermediary variables including customer attitude, according to Ramayah et al. (2005). Upon realizing the potential advantages of the new system, users are anticipated to embrace it. According to motivational theory, their views will probably coincide with their desire to utilize the system once they see its value, which is consistent with the idea of extrinsic motivation (Ryan and Deci, 2000). Consequently, the following hypothesis is put forth:

H_1: Perceived ease of use has a significant impact on perceived usefulness

Perceived Ease of Use and Usefulness and E-CRM

The term Electronic Customer Relationship Management (E-CRM) describes the electronic application of CRM using web browsers, the internet, and other electronic media, such as contact centers, email, and customization (Harrigan & Miles, 2014). E-CRM is a web-based approach that businesses use to improve their interaction with their clients (Bezhovsk et al., 2016). Improving customer satisfaction and fostering customer loyalty are the main objectives (Hamid et al., 2015). The internet is an essential conduit for information and commerce, allowing companies to use it as a tool for customer relationship management, according to research by Harrigan & Miles (2012). The investigation examines the characteristics of E-CRM seen on business websites in order to determine how E-CRM and customer happiness are related. The results highlight the significance of strategic electronic relations management in modern company settings by highlighting how the successful integration of E-CRM features may result in improved client involvement, fulfillment, & commitment.

Measuring CRM performance within organizations is crucial for enhancing revenue and fostering customer loyalty. As customer needs evolve and become more sophisticated, E-CRM technologies must also advance to effectively address these demands. Al-Qeed et al. (2017) emphasized that consistent utilization of CRM technology significantly influences overall CRM performance. They suggest that a more comprehensive and advanced CRM technology correlates positively with performance across various stages of the customer lifecycle. This implies that organizations employing sophisticated CRM solutions are likely to witness improved customer relationship outcomes. Furthermore, the effectiveness of CRM technology plays a critical role in enhancing customer relationship performance, reinforcing the necessity for businesses to invest in and adopt advanced E-CRM systems. By doing so, companies can better engage with customers, tailor experiences, and ultimately achieve higher satisfaction and retention rates, marking the importance of continual improvement in CRM technology for sustained success in customer relationship management.

H_2: Perceived ease of use has a significant impact on E-CRM
H_3: Perceived Usefulness has a significant impact on E-CRM

E-CRM and Customer Loyalty

In the context of Electronic Customer Relationship Management (E-CRM), relationships with customers are more than just transactions. It embodies a customer's emotional connection, trust, and dedication to a particular online brand or organization. This loyalty is evident through the customer's consistent engagement with the brand's digital platforms, purchasing behaviors, transactional activities, and sustained interactions over time. Studies conducted by Larsson and Viitaoja (2017), Tariq et al. (2019), and Guerola-Navarro et al. (2022) highlight that effective E-CRM strategies are crafted to foster customer loyalty through a variety of approaches. These strategies prioritize the provision of personalized experiences, relevant content, exemplary customer support, and customized offerings. Such coordinated initiatives play a vital role in establishing strong and lasting relationships between companies and their online clientele. By emphasizing personalized interactions and addressing customer needs in a significant manner, organizations can cultivate enduring loyalty among their customers. Prior research has highlighted the significance of customer loyalty, especially within the service sector, which recognizes it as a vital component (Ahmed, 2020; Khan et al., 2020). Customer loyalty represents an emotional connection between businesses and their clients, characterized by a preference for continued patronage over competitors, driven by satisfaction and trust in the services provided (Ullah et al., 2020). In the current landscape of intense competition and uncertainty most notably within the airline industry—

increasing customer loyalty has become a strategic necessity for achieving sustainable success. Nevertheless, So et al. (2016) found that a well-informed customer base tends to exhibit lower levels of loyalty, underscoring the need for continuous efforts to adapt to evolving customer expectations.

Enterprise Resource Management (ERM) enhances customer loyalty by enabling personalized interactions, facilitating timely communication, implementing targeted marketing strategies, and leveraging data-driven insights (Oumar et al., 2017). By creating meaningful online experiences, businesses can cultivate robust and lasting relationships with their digital customers (Al-Omoush et al., 2021; Law, 2017; Yang & Babapour, 2023). Oliver's (1999) conceptualization of customer loyalty underscores a genuine commitment to continually engage with a brand, regardless of external factors or promotional efforts that might tempt customers to switch brands. Since e-loyalty depends on online consumer Relationship Management (e-CRM), it is clear how important it is to cultivate and maintain consumer loyalty in the world of digital commerce.

H_4: E-CRM has a significant impact on customer loyalty

Intention to Adopt AI Intelligence

Artificial Intelligence (AI) is regarded as a computer program capable of self-operation without human intervention (Turing, 1956). In the commercial world, companies have to manage enormous amounts of client data, which calls for IT assistance (Bose, 2002). It is difficult to handle such huge datasets with only human labor, even if thorough analysis of consumer data is essential. AI solutions are necessary in this situation (Fotiadis and Vassiliadis, 2017).

Studies show that by examining customer data, businesses may get insight into consumer behavior, which can help them improve customer outreach and streamline operations (Graca et al., 2015). Accordingly, good customer data analysis is essential for determining customer needs and aversions, which helps businesses customize their tactics in a way that maximizes productivity and yields measurable results (Wen and Chen, 2010). client relationship management (CRM) systems that use AI can analyze client data more quickly and affordably, which will improve organizational performance (Maxwell et al., 2011; Chatterjee et al., 2020b). IDC Report (2017) found that 28% of 1,028 multinational companies had already used AI-integrated CRM systems, and 41% intended to do so by 2019. The faster development of AI integration in CRM systems is demonstrated by this data (Graca et al., 2015). Employee adoption and willingness to utilize this technology are critical to its successful deployment (Flandorfer, 2012). If organizational employees believe that a new system would directly improve their workflow and reduce their workload, they are more likely to accept it, according to research.

H_5: Intention to Adopt AI moderate impact on Customer Loyalty

Conceptual Model

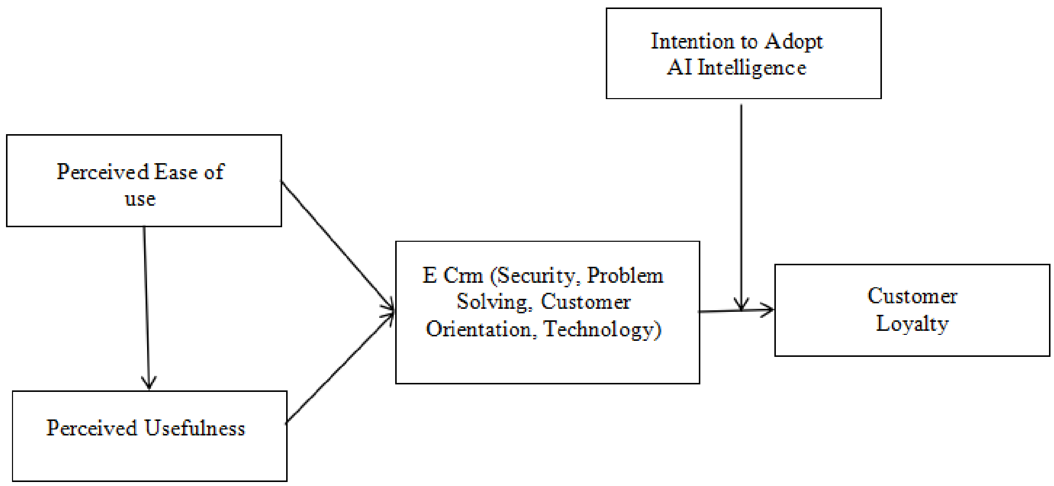


Figure 2.4: Research Model adopted from (Noreen et al., 2023) (Shaikh et al., 2024)

Methodology

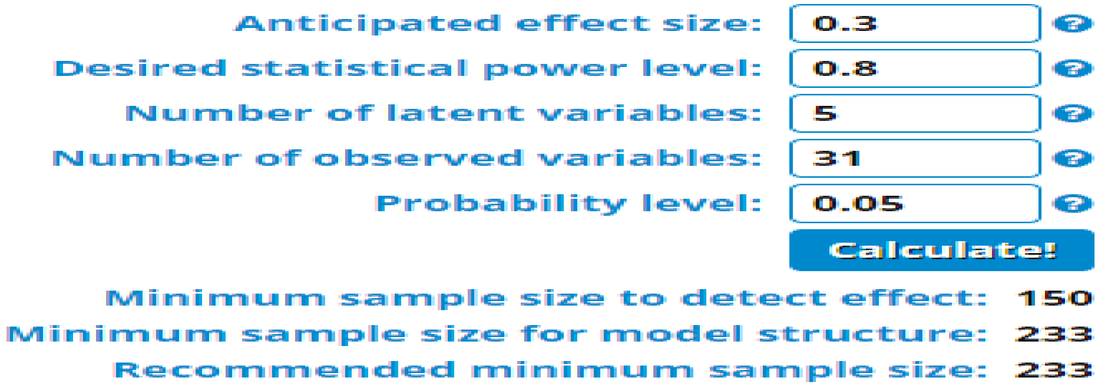
The research approaches used will be described in the study's third chapter. Whether the emphasis is on qualitative insights that aim to comprehend experiences and perspectives, or quantitative analysis that prioritizes numerical data and statistical interpretation, it will be recognized. In addition, this chapter will describe the tools and methods used for data analysis, such as surveys, interviews, and other information collection methods.

There are two main methods in research that are acknowledged: qualitative and quantitative. According to Veal (2005), the qualitative approach focuses on gathering and analyzing details which cannot be easily measured, whereas a quantitative strategy involves using statistical techniques to analyze data. Statistical tools and data analysis approaches will be used in this quantitative investigation. Research can serve various purposes, categorized as descriptive, exploratory, or explanatory. Descriptive research seeks to delineate and clarify the characteristics of a specific group or phenomenon. Exploratory research aims to uncover new areas or gather information that may be poorly understood. Explanatory research focuses on investigating relationships to enhance understanding (Cooper, Schindler, & Sun, 2006). This study is classified as explanatory research, with the goal of examining the impact of specific variables.

Research Design

The research design is crucial in facilitating a comprehensive understanding of the research question through the collected evidence. In the context of social science research, the acquisition of evidence generally entails identifying the appropriate type of evidence necessary to assess a hypothesis, evaluate a program, or accurately represent a phenomenon. This particular research design is characterized as informal, aiming to comprehend phenomena via conditional statements. Through the examination of causal effects, it can illuminate how one variable (independent) may induce variations or exert influence on another variable (dependent).

Sampling



Selecting an accurate portion of a population from which to make generalizations about the total population depends critically on the sampling process. Sample methods may be divided into two main categories: probability sampling and non-probability sampling. A convenience non-probability sampling technique was used in this investigation. Furthermore, the questionnaire included a Likert scale, asking participants to rate their agreement or disagreement with a range of propositions on a scale from 1 to 5. By speaking with each respondent directly, this survey method makes it possible to get primary data (Szajna, 1996; Wu and Wang, 2005). The material collected especially for the purposes of the present research is referred to as primary data. The data was collected from private banks, which operates as a commercial bank. This classification is significant as the operational framework and employee structure may vary between commercial and private banks.

A purposive sampling technique was employed to select participants directly involved in banking operations and management. The sample included employees from different levels of management within the bank, ensuring a broad representation of perspectives. Participants were categorized into entry-level employees, mid-level management, and senior executives, allowing the study to capture insights from various levels of experience, responsibilities, and decision-making roles. This approach ensured a comprehensive understanding of the factors influencing banking operations and management.**3.6.3**
All participants in this study were confirmed as employees of private banks. Their management levels were classified based on their job responsibilities, tenure, and hierarchical position within the bank. This classification allows for a structured analysis of how different job roles influence employee satisfaction and its subsequent impact on organizational performance.

Statistical Model
Using SMART PLS software, the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach is applied for hypothesis testing. The effectiveness of PLS-SEM in supporting SEM-based research is the reason it was selected. Many academics like this statistical tool because of its advanced technology and reliable software features for testing hypotheses.

Perceived Ease of Use (PEU): This variable denotes the degree to which users perceive that utilizing a new system will require minimal effort. It is linked to the concept that technology should be straightforward to learn and operate, which can profoundly impact users’ attitudes toward adopting the technology (Venkatesh & Davis, 2000).

Perceived Usefulness (PU): This variable reflects the extent to which users believe that utilizing a specific system will improve their job performance. The greater the users' perception of a system's usefulness, the more inclined they are to adopt it. This variable plays a pivotal role in influencing the intention to use AI-integrated systems within the banking sector (Davis et al., 1989)..

Intention to Adopt AI (IAI): This variable signifies the user's readiness to utilize AI technologies in their banking activities. It encapsulates the behavioral intention of users to interact with AI-integrated Customer Relationship Management (CRM) systems, driven by their perceptions of ease of use and perceived usefulness (Jackson et al., 2013).

Electronic Customer Relationship Management (E-CRM): E-CRM refers to the utilization of digital technologies for managing customer relationships and interactions. It includes a range of online tools and platforms that promote communication and service delivery, with the ultimate goal of improving customer satisfaction and loyalty (Nafez et al., 2023).

Customer Loyalty (CL): This variable signifies the degree of customer commitment to the sustained utilization of a specific bank's services over an extended period. It is frequently assessed through customers' propensity to engage in repeat transactions and their likelihood of endorsing the bank to others, serving as an indicator of their overall satisfaction and trust in the banking services offered (Anderson et al., 2003).

Ethical Considerations

The study team made sure that all decisions were made with ethics in mind. completed this study by following the supervisor's appropriate research guidelines. Every response to the surveys was gathered in a way that made sure no one was coerced or under any duress to answer the questions. To ensure that respondents do not feel pressured, allow ample time for them to complete the questions. All of the respondents' information and comments were kept private both throughout and after the study. Every piece of data utilized has been appropriately cited to guarantee that all credits were given where they were due.

In this chapter, discussed the methodologies used in this study. Introduced the research design, research methodology, research purpose, and data collection technique. Also highlighted the importance of ethical considerations in this study. Overall, this chapter provides a comprehensive understanding of the methods and techniques employed in this research.

Results and Discussion

Pilot study

The results of the reliability analysis using Cronbach's alpha for the pilot research are shown in Table 4.1.

Table 4.1: *Pilot Study (n = 50)*

Variable Name	N Items	Cronbach's Alpha
Perceived Ease of Use	5	0.831
Perceived Usefulness	5	0.859
Intention to Adopt AI Intelligence	3	0.853
E CRM	13	0.945
Customer Loyalty	5	0.890

Hair et al. (2018) suggested that a variable's reliability test Cronbach's alpha coefficient should be more than 0.70 in order for it to have sufficient internal consistency. As can be seen from the accompanying table, the majority of the factors in question have achieved substantial consistency internally.

No missing values were discovered in the 300 responses that were gathered from the sample population. 15 univariate outliers with a Z Score more than ± 3.29 and 21 multivariate outliers with a Mahalanobis Distance (D2) less than 0.001 were discovered by the investigation, albeit (Hair et al., 2018; Tabachnick & Fidell, 2021). 264 valid and useable responses for main-study analysis were left in the final sample after outliers were eliminated.

Demographic Profile

Table 4.2 presents the demographic profile of the 264 participants in this research.

Table 4.2: *Demographic Profile (n = 264)*

		Frequency	Percent
Gender	Male	160	60.6
	Female	104	39.4
Age	18-25	71	26.9
	26-35	144	54.5
	36-45	40	15.2
	46-65	6	2.3
	65 and above	3	1.1
Education	Intermediate	31	11.7
	Bachelor's Degree	101	38.3
	Master's Degree	120	45.5
	PhD	12	4.5
Online Transaction Frequency	1 to 9	111	42.0
	10 to 19	101	38.3
	20 and above	52	19.7

Among the 264 participant surveyed, the gender distribution reveals that 160 individuals are male, constituting 60.6% of the sample, while 104 individuals are female, making up 39.4%. The age distribution shows that the largest age group is 18-25 years, comprising 26.9% (71participants), followed by 26-35 years at 54.5% (144 participants). Smaller proportions are seen in the age groups 36-345 years (15.2%, 40 participants), 45-65 years (2.3%, 6 participants), and 65 or above (1.1%, 3 participants). In terms of education, 11.7% (31 participants) are intermediate, 38.3% (101 participants) are graduates, and 45.5% (120 participants) have master's degree. Regarding online transaction, 42.0% (111 participants) 1 to 9 times, 38.3% (52 participants) 10 to 19 times.

Reliability Analysis

A measurement model utilizing the PLS algorithm approach is presented in Table 4.3.

Table 4.3: Measurement Model

	Outer Loading	Cronbach Alpha	CR	AVE
CL1	0.785	0.846	0.860	0.618
CL2	0.805			
CL4	0.824			
CL5	0.812			
ECRM10	0.793	0.882	0.884	0.630

ECRM11	0.817			
ECRM12	0.796			
ECRM5	0.794			
ECRM8	0.737			
ECRM9	0.822			
IAI1	0.838	0.798	0.825	0.708
IAI2	0.860			
IAI3	0.825			
PEU1	0.721	0.746	0.759	0.632
PEU2	0.757			
PEU5	0.727			
PU1	0.714	0.799	0.801	0.551
PU2	0.757			
PU3	0.723			
PU4	0.761			
PU5	0.754			
AI x ECRM	1.000			

For acceptance, Hair et al. (2011b) suggested that all exterior loading values be more than 0.70. Additionally, according to Hair et al. (2011a), VIF values have to be lower than 5. A likelihood level of less than 5% is also recommended (Hair et al., 2011b). All of the VIF values in the preceding table are less than 5, hence the study may go on to hypothesis testing. The internal consistency of the constructs was also evaluated by calculating Cronbach's alpha (α). Values over 0.9, 0.8, and 0.7 were categorized as outstanding, good, and acceptable, respectively, in accordance with the guidelines recommended by George and Mallery (2003). Composite reliability is deemed acceptable when it exceeds the cutoff value of 0.7, and the average variance extracted (AVE) must be at least 0.5 (Hair et al., 2011a).

Fornell and Larcker (1981) Criterion

Table 4.4 shows the result of FLC for discriminant validity assessment.

Table 4.4: Fornell-Larcker Criterion (FLC)

	CL	**ECRM**	**AI**	**PEU**	**PU**
CL	**0.786**				
ECRM	0.710	**0.794**			
AI	0.455	0.461	**0.841**		
PEU	0.369	0.544	0.521	**0.703**	
PU	0.339	0.373	0.617	0.530	**0.742**

The squared-root AVE of the constructs (bold diagonal values) in the table shown above is greater than the corresponding horizontal (Hair et al., 2011b) and vertical correlation (non-bold) values; hence, discriminant validity using the FLC approach has been satisfied (Fornell & Larcker, 1981).

Table 4.5 shows the result of crossloadings for discriminant validity assessment.

Table 4.5: Crossloadings

	CL	ECRM	AI	PEU	PU	AI x ECRM
CL1	**0.785**	0.496	0.268	0.207	0.213	0.144
CL2	**0.805**	0.563	0.304	0.328	0.264	0.241
CL4	**0.824**	0.669	0.471	0.375	0.244	0.034
CL5	**0.812**	0.573	0.432	0.286	0.341	-0.055
ECRM10	0.507	**0.793**	0.355	0.437	0.260	0.013
ECRM11	0.648	**0.817**	0.265	0.372	0.297	0.007
ECRM12	0.620	**0.796**	0.438	0.486	0.251	-0.016
ECRM5	0.533	**0.794**	0.352	0.485	0.346	0.023
ECRM8	0.510	**0.737**	0.426	0.421	0.327	-0.052
ECRM9	0.548	**0.822**	0.361	0.383	0.297	-0.051
AI1	0.291	0.265	**0.838**	0.402	0.530	0.103
AI2	0.456	0.457	**0.860**	0.379	0.457	-0.018
AI3	0.366	0.401	**0.825**	0.543	0.589	0.138
PEU1	0.172	0.310	0.305	**0.721**	0.335	0.135
PEU2	0.190	0.330	0.429	**0.757**	0.373	0.168
PEU5	0.403	0.513	0.450	**0.727**	0.475	0.120
PU1	0.177	0.292	0.443	0.466	**0.714**	0.147
PU2	0.246	0.327	0.500	0.425	**0.757**	0.077
PU3	0.294	0.186	0.409	0.400	**0.723**	0.309
PU4	0.216	0.297	0.417	0.365	**0.761**	0.292
PU5	0.364	0.259	0.522	0.265	**0.754**	0.260
AI x ECRM	0.118	-0.015	0.077	0.179	0.280	1.000

As previously said (Hair et al., 2011b), the table implies that discriminant validity may be achieved when bold values are displayed to be greater in their concept than other values.

HTMT Ratio

The HTMT ratio for the PLS algorithm-based discriminant validity evaluation is displayed in Table 4.6.

Table 4.6: *HTMT Ratio*

	CL	ECRM	IAI	PEU	PU	AI x ECRM
CL						
ECRM	0.806					
AI	0.520	0.529				
PEU	0.427	0.646	0.661			
PU	0.425	0.436	0.780	0.647		
AI x ECRM	0.171	0.037	0.115	0.208	0.326	

The results of assessing discriminant validity using the Heterotrait-Monotrait (HTMT) ratio are shown in Table 4.6. In order to guarantee satisfactory distinction across latent constructs, Henseler et al. (2016) and Henseler et al. (2015) advise that the HTMT ratio not surpass 0.90.

Predictive power

Table 4.7 displays the endogenous components' predictive power in the structural model that is based on the PLS algorithm and PLS blindfolding techniques.

Table 4.7: *Predictive Power*

Variables	R-square	Q²predict
Customer Loyalty	0.538	0.160
ECRM	0.305	0.262
Perceived Usefulness	0.281	0.227

Falk and Miller (1992) suggested that for the variance explained of a certain endogenous component to be considered appropriate, R2 values should be equal to or greater than 0.10. For endogenous latent variables, Chin (1998) suggested that R2 values be less than or equal to 0.19, higher than or equal to 0.67, or moderate, and more than or equal to 0.33. Given that they are greater than 0.33, the first three R-squared values in this case have been deemed moderate.

Direct-effect analysis

Table 4.8 shows the result of direct-effect analysis using PLS bootstrapping.

Table 4.8: Direct-Effect Analysis using PLS-SEM

	Original sample	T statistics (|O/STDEV|)	P values	Result
ECRM -> CL	0.643	7.882	0.000	Supported
AI -> CL	0.149	1.652	0.099	Not Supported
PEU -> ECRM	0.481	5.234	0.000	Supported
PEU -> PU	0.530	6.633	0.000	Supported
PU -> ECRM	0.118	1.193	0.233	Not Supported
AI x ECRM -> CL	0.124	1.714	0.087	Not Supported

CL = Customer Loyalty; PEU = Perceived Ease of Use; PU = Perceived Usefulness; AI = Intention to Adopt AI Intelligence

According to the above table, ECRM significantly and favorably affects CL ($p < 0.000$). AI positively and negligibly affects CL ($p > 0.099$). PEU has a strong and favorable impact on ECRM ($p > 0.000$). PEU has a strong and beneficial impact on PU ($p < 0.000$). PU has a favorable and negligible impact on ECRM ($p < 0.233$). CL is moderately and insignificantly impacted by AI x ECRM ($p > 0.087$).

Conclusion

From the establishment of traditional banking methods introduction of AI-based banking in 2017 (Noreen et al., 2023), the banking industry has undergone a slow progression. With notable improvements taking place in areas like core banking, operational performance, and customer service, this signifies a substantial shift in the sector. This study aims to comprehend client aspirations regarding AI adoption in the banking industry as well as the difficulties related to integrating AI. As a result, an explanatory strategy was used, employing a quantitative research design to investigate the connections between independent variables/predictors (perceived usefulness, perceived ease of use, and ECRM) and dependent variables (perceived usefulness, ECRM, and buyer devotion) in the context of AI the adoption process. A moderating influence is also thought to be the aim to use AI. In banking, AI technology increases client loyalty. Acceptance of AI is correlated with familiarity and contentment. In general, happy customers are more open to new AI developments. On the other hand, client satisfaction from inperson contacts is not necessarily equal to that of digital customer service. Although artificial intelligence (AI) is very good at organizing data and optimizing digital processes, research indicates that it cannot completely replace human customer care agents. However, it has been demonstrated that AI may save time in banking procedures. Because of AI, the banking industry is changing significantly and has a lot of room to expand. It is important to concentrate on reducing the risks connected with its application, even if artificial intelligence (AI) presents benefits in fields including fraud detection, claims administration, pricing, risk management, and consumer interactions. In order to increase operational efficiency, reduce expenses, and improve customer happiness, the Indian banking industry is progressively implementing AI. Instead of replacing human skill, artificial intelligence is seen as a useful technical assistance. The focus is on providing individualized, high-quality services in a timely way. Relationship building, strategy development, team leadership, and growth all depend on human responsibilities, even in the face of tremendous technical breakthroughs. The best ways to use AI are still being sought for by financial organizations. It's vital for banks to strike a balance between the efficiency that AI offers and the customers' desire for human interaction.

Managerial Implications

For government agencies, banking management, legislators, and technology regulatory authorities, this report offers useful implications and suggestions. To reduce the dangers involved with adopting digital technology for transactions, banks management may use the findings to update and improve their marketing tactics in order to increase and foster client trust. In order to improve security and protection, the report also suggests that regulatory bodies and bank management take the appropriate actions. Enhancing these areas would boost the dependability and appeal of AI in financial services while also guaranteeing improved client service. Perceived utility (PU), according to the suggested model, is a key indicator of the banking industry's adoption of AI-integrated CRM systems. Accordingly, people are more likely to want to utilize and accept the system the more they understand its value. Therefore, the banking industry's top management should inform the appropriate staff members about the benefits and efficacy of this new method. Sharing success stories of other firms' successful system implementations will help achieve this. Additionally, the study highlights that the adoption of AI-integrated CRM systems in enterprises is influenced by perceived ease of use (PEU). This suggests that the technological features of the system are highly valued by consumers. Therefore, in order to simplify the exploration and use of the system, banking sector management must make sure that developers and system designers are vigilant in minimizing its complications. Both perceived utility (PU) and perceived ease of use (PEU) are significant factors affecting users' behavioral intentions to use AI-integrated CRM systems, according to the suggested model. Supervisors in the banking industry should work hard to influence workers' opinions about the new system in a good way. The absence of unfavorable social feedback that would discourage consumers from using this technology is vital.

Limitations of the study

There are significant limitations to this research. First off, because the study was carried out in Karachi, its conclusions might not be as applicable to other areas or nations. It would be crucial to look into if comparable outcomes are seen in other places, especially considering Karachi's distinct organizational, cultural, and economic circumstances. Therefore, the results can be regarded as location-specific. Second, the study's design meant that data was gathered all at once, which raises the risk of cross-sectional timing bias. Notwithstanding its merits, this research has many shortcomings. The validation of the model only included input from 300 respondents, which could not be enough to fairly reflect society as a whole; this issue should be addressed by future studies. Furthermore, the investigation only included data from 20 organizations, which might not give a whole picture of the issue. Future research ought to think about broadening this focus. Additionally, the suggested model has a 67% explanatory power. Other boundary conditions, such trust-related elements, might be included in the future to determine if they increase the model's capacity for explanation.

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