Optimizing Customer Experience in Digital Banking: A Comprehensive Study on AI-Powered Personalization and Efficiency

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A DISSERTATION

Presented to the Department of
Software Engineering
program at Selinus University

Faculty of Computer Science
in fulfillment of the requirements
for the degree of Master of Science
in Software Engineering

2024

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Acknowledgement

First is my thanks and appreciation to God and all those who helped me in my research, Data gathering especially my dear friend in whom I found a brother Mr. Sami from Culcutta for helping me in gathering of Data. I really appreciate your help, effort and trust. You have been supportive, a tower of strength from the first day we met, about 15 years ago when I step my foot in India to study computer electronics. From been the son of my land lord to a friend and a brother. I pray for your health and success.

To all those who stood by me and encourage me both physically and financially, I thank you very much Mr. Aziz of MediaHoek BV. Den Haag , without you, it would have been difficult.

Abstract

This research study reviews the customer experience and its optimization with the AI-enabled personalization and efficiency in the banking industry. The customer dataset of Indian banking institutions employed in this study to determine the impact of AI on customer experience, trust, and satisfaction in banking industry. The gap between financial institutions and its customers is fulfilled with the personalized services to establish the customer trust. If customers trust the banking services and financial products, they are more willing to provide their personal data to receive the customized banking services to enhance the customer value. Accordingly, the Artificial Intelligence (AI) technology can assist the digital banks to tailor the related products and services to their consumers and enhance the customer experience through the efficiency gains of compliance, risk management, and fraud detection capabilities with the incorporation of chatbots. The previous studies limited to provide the comprehensive understanding of the AI-based digital finance and its impact on customer experience through the personalization, trustworthiness, privacy, and risk mitigation. To address these research gaps, this research study will provide the data findings to develop the transparent, user-centric, ethical, and trustworthy AI-based customization metrics in digital banking. These investigations will explore the improved personalization and user trust in the AI-enabled customer experience in digital banking.

The AI-based customer experience has been analysed with the established classifiers of Natural Language Processing (NLP), such as k-Means clustering, Hierarchical Agglomerative clustering, and Density-based Spatial Clustering of Applications with Noise (DBSCAN). An optimal performance of the model was showed that giving the zero noise points for k-Means clustering and Hierarchical Agglomerative clustering while the noise points were higher for DBSCAN, i.e. 2710. The greatest value of Silhouette index was reported for hierarchical clustering with 0.4194 than the k-Means and DBSCAN clustering methods that resulted Silhouette values as 0.218 and 0.1805, respectively. The Hierarchical Agglomerative clustering of NLP is foreseen is the most appropriate and efficient approach to investigate the customer needs and preferences for personalized strategies to achieve the customer satisfaction and trust.

Keywords:

AI-enabled Customer Experience, Customer Satisfaction, User Trust, Artificial Intelligence, Natural Language Processing, Clustering Methods, Personalization, Digital Banking

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Chapter 1: Introduction

The banking industry has been facing several challenges in adapting with the emerging trends that helps them maintaining profitability. There are various areas to be focused on when elaborating marketing and business strategies including, financial deregulation, contend with other shadow banking and FinTech systems, coping up with digitalization, and meeting the ever-changing demands of end-users regarding the quality of bank services. From a broader context, the main challenges that banks face has been related to maintaining the marketplace share and enhancing performance indicators. In order to cope up with these, digitalization offers the banking sector a fierce competitive nature, where they can maintain their position against other shadow banking institutions and FinTech organizations. However, bank users in regional economies nowadays have become more educated and desirable, witness increase in the levels of financial literacy, offer comparative and contrasting nature within themselves regarding different bank services, and moreover, the accessibility of bank services becomes simpler and easier. Conversely, the banking industry prohibits a substantial variation in their services provided, highlighting the significance of factors that impact the end-user's satisfaction and the banking institutions' desire to find ways that helps to guarantee the retention of customers (Badea et al., 2021).

1.1 Research Background

1.1.1 Digital Transformation in the Banking Sector

The growing trends in the Internet over the past few decades have caused the banking institutions to develop new technologies and services that fulfill the changing needs of customers, as argued by Martins et al. (2014). One such significant technology they provide is the digital banking (DB) where it offers banking services digitally to the users. Dootson et al. (2016) argued that since banks work in changing user interfaces based on the users' preferences, the marketing activities of banking institutions have been significantly impacted by the DB services. Since banking institutions operate in a competitive market, the DB services provide various economic implications and thus becomes a strategic competitive tool. The financial services provided through DB have become beneficial for both banks and their users. Nonetheless banking institutions face various challenges as a result of DB transformation brought about by ever-changing demands of end-users, especially with regards to service delivery. Monferrer-Tirado et al. (2016) argued that post 2008 financial crisis, banking institutions faced immense competition in meeting the demands of customers, enhancing profitability, and maintaining the retention rate of customers.

The conventional banking services have been outperformed by various services offered through DB, like t-banking (telephone), e-banking (internet) and m-banking (mobile phones), to their users regarding to service delivery. The idea of offering services through phones, first introduced by First Direct in pre-1990s, gave rise to digital banking (Oliveira & von Hippel, 2011). According to Cortiñas et al. (2010), French et al. (2013) and Manser Payne et al. (2017), DB changed how banks engage with their users by enabling them to provide multi-channel integrated services. Research into DB services has thus become increasingly important to know the full potential of banks.

The way that banking services are being transformed by DB has significantly impact the community as a whole. According to Teo et al. (2014), digital services are constantly being used by banking organizations for creating new revenue streams and improving the customer service efficiency. As a result, in order to remain competitive in the marketplace, all organization should implement digitalization concepts. Given the changing demands of customers, banking industry must pay attention to DB services with the goal of enhancing the experience of their customers. Due to its significant impact on user's accessibility of financial services, various studies such as Xue et al. (2011), Hanafizadeh et al. (2014), and Jun and Palacios (2016) focused on digital banking and its services provided to their users. On the contrary, Hoehle et al. (2012) in their study about adoption and utilization of digital banking argued that study phenomenon and methodologies employed in earlier studies had their own limitations. Hence, the current study made an attempt to gain knowledge from several theories and models, such as business performance, technological innovation, and service quality to explore the association between DB services and customer experience, personalization, and organizational efficiency.

1.1.2 Characteristics of Digital Banking Channels

The functional components like service quality have been significantly impacts the DB that appeal to banking institutions and their users, as argued by Amin (2016) and Jun and Palacios (2016). The bank users can take advantage of multiple services since it has been offered through DB. For example, one can involve in banking activities, chatting, and web browsing parallelly. Banking customers can use telephones for carrying out transactional activities via telephone banking (Sundarraj & Wu, 2005). Internet banking offers different services to be provided with high number of advantages since technology has become more accessible and user-friendly from any location. Customers can make use of almost all services conveniently from their home due to the internet banking facilities (Mols, 2001; Yiu et al., 2007; Martins et al., 2014). Moreover, with the use of mobile banking, financial services can be offered via mobile devices. The capability of customers in performing remote tasks has led to an increase in the mobile banking. Various user interfaces (browsing and dialing methods) have been provided by these digital channels (Tam & Oliveira, 2017).

The terms “t-banking”, “m-banking”, and “e-banking” refer to the telephone banking, mobile banking, and internet banking respectively (Lin, 2011; Sarokolaei et al., 2012;

Hanafizadeh et al., 2014). The primary difference between these DB and other services is the transmission medium (for example, e-banking or m-banking). Digital services have been also unstable, non-tangible, and cannot be inventoried. They can be used as they are produced. Differences in the quality of services might arise from the way banks and their users engage during the process of delivering services (Amin, 2016). The expectations of customers regarding banking services vary substantially, and the degree to which service providers meet those expectations have been used to determine the satisfaction among customers. Hence, it has been crucial to study the factors that influence DB services with regards to loyalty, satisfaction, and experience of customers in the banking institutions.

Digital innovative capabilities offer banking industry to create innovative services that meet the expectations of their users. An example of where an individual does not have to go banks and stand in queues to make transactions is due to the DB services. Operational efficiency can be ensured here by decreasing the number of bank branches. Researches into DB adoption have been particularly interesting due to its features offered and the way banks have transformed (Yoon, 2010; Alsajjan & Dennis, 2010; Hanafizadeh et al., 2014). However, the characteristics of DB services have not been taken into account in these studies. Other researches such as Yee et al. (2010) and Klaus & Maklan (2013) have only concentrated on enhancing the economic values of banks and customers, and not the DB services offered.

An individual can pay their bills, transfer money and check bank balances through the use of DB activities. It has significantly impacted the electronic commerce by making electronic payments. Given these characteristics, DB has become an appealing option for physical bank branches and is worthwhile area for conducting research and also aids banking institutions to develop their skills and knowledge. DB can also provide mutual gain, better customer services, relationship maintenance, enhanced customer experiences. However, DB services have been widely acknowledged due to its characteristics, further research is needed to determine whether or not the functional and service characteristics and convenience have an impact on the customer experiences (Keisidou et al., 2013; Monferrer-Tirado et al., 2016).

1.1.3 Application of AI Technologies for Customer Experience

According to Indriasari et al. (2019), financial services are currently become customer-focused due to the developments of various artificial intelligence (AI) techniques such as machine learning (ML), neural networks (NN), computer vision, intelligence automation, deep learning (DL) and natural language processing (NLP). Some of the well-prominent banks employ AI technologies for the purpose of different functions, shown in Table 1.

Table 1: Role of AI in different banks

BANKS	ROLES
JPMorgan	Automation of bank services.
City Bank	Detection of fraudulent activities.
Wells Fargo	User-friendly mobile applications to attract new customers, particularly millennials.
JPMorgan Chase	
Bank of America	AI-powered chatbot applications that provide written and spoken financial support.

Self-service technologies (SSTs) are interfaces that allow users in obtaining banking services without requiring the assistance of any employees, and thus act as a means of increasing the banking experience of customers (Meuter et al., 2000; Curran & Meuter, 2005). According to Berry et al. (2002), SSTs offer constant flow of experiences, where it may be positive, or negative, or both. Kim and Yang (2018) argued that SSTs provide increased efficiency by decreasing the operational costs of banks by making substantial investments on AI applications and ensuring a sufficient return.

Chatbots has been the most common AI application that employed in most banks. Schlicht (2016) defined chatbot as an AI service that offer chat-based interface to handle user queries. Desaulniers (2016) stated AI-powered chatbot applications have been the simpler and easier way of managing the users' needs. However, according to Dreyer (2016), chatbot applications have not always been the best solution, especially for handling complicated queries. Some users prefer interactive voice response (IVR) application to chatbots, since they perceive often chatbots as most annoying. In addition, they questioned the accuracy of the information offered by these chatbot applications (Dreyer, 2016).

The key factor in determining the performance of chatbot applications will then be providing the end-users with all the information at the appropriate moment, in the appropriate manner, and in the appropriate context. In addition, the experiences of users may be significantly impacted by their understanding on technologies. For example, low-quality information might lead to higher maintenance and operational costs (Trivedi, 2019). Other factors such as assurance, empathy, and responsiveness needed are also being impacted by poor use of technologies (Gorla et al., 2010). Ultimately, banking institutions should take into account the performance, social, psychological, time, and financial risks associated with the implementation of different AI solutions in banking operations (Lai-Ming Tam, 2012).

1.2 Problem Statement

The problem statement identifies the various factors concerning the existing circumstances for which the study is being conducted. It emphasizes that a theory needs to be verified or that decision-making or policy challenges in practice need to be addressed. All the organizations in the banking sector have been facing immense rivalry as a result of globalization and trade liberalization. These organizations must take strategic decisions with their existing goods and services to hold a constant market share. On the other hand, the banking sector has been experiencing high competition with regards to the perception of quality of services. For holding steady position in the marketplace, it was recommended that service quality should be the main factor in their marketing efforts of banks. There are multiple levels of service quality, and the significance of each level varies amongst individuals. Every bank has acknowledged that they fit at least one of the service quality factors. Organizations have paid close attention to bank services since determining which one to evaluate higher than another depends on various elements, like service quality, interest rates, and location of the banks. Studying the evolving demands of customers, implementing innovative financial tools, utilizing the IT services are all become crucial for the domestic banks to remain competitive in the scenario brought on by the entry of foreign organizations. As almost all banking institutions have same kind of technologies, it has been believed that a banking organization can only thrive in the competition only by offering optimized customer experience services to their users. For this reason, it has been essential to identify whether the banks can meet the requirements of providing quality services and meet the demands of customers. Restructuring policy options of banking organizations for their market survival can be supported by creating distinct strategic groups within the financial sector and establishing themselves based on the diverse perspectives of customers. In order to improve their financial performance, the banking institutions had to make use of their current resources, keep providing the high service quality efficiently, and adapt to changing business needs. The current scenario necessitates evaluating quality of services with regards to the changing demands of customers and operational efficiency in order to assist banking industry in increasing customer satisfaction levels and improving service quality while maintaining the retention rate of customers.

1.3 Research Aim and Objectives

The aim of this study is to employ AI to provide customised approaches that improve user experience, expedite procedures, and ultimately strengthen bonds between customers and digital banking platforms. The following are the objectives of this study:

1) To evaluate the impact of AI-powered personalization on customer satisfaction.

2) To assess the efficiency gains through AI integration in digital banking operations.

3) To examine the factors influencing user trust in AI-enhanced digital banking environments.

1.4 Research Questions

The research questions for this study are:

1) How does the implementation of AI-driven personalization in digital banking systems affect customer satisfaction and engagement?

2) What are the quantifiable efficiency improvements achieved by integrating AI technologies in various aspects of digital banking operations?

3) What factors contribute to or hinder user trust when AI is employed for personalization and efficiency in digital banking, and how can these factors be addressed?

1.5 Need for the Study

Banking institutions must employ efficient strategic initiatives with an aim to provide high quality services. In the banking industry, the ability to differentiate different banks can be understood by the level of service quality they offer. Thus, maintaining the high standard of customer service has been crucial for the successful outcome of businesses, since it attracts new banking users, fosters strong relationship with current banking users, reduces the attrition rate, increase the competitive ideas of individual banks, and reduces the need for high-cost products or service redesigns. Increasing the attrition rate and reducing the retention rate has always been an important factor for the banking institutions to hold their positions in the industry, with quality of banking services offered has been found to be the main factor. However, it is still unclear that what expectations that the customers had concerning the service quality, and how banks perceived quality service. Hence, the current study made an attempt to investigate the experience of customers with regards to the personalized quality of services provided by banks through AI applications and ultimately increasing the overall operational efficiency. It also focusses on determining which service quality factor used to increase customer experience in the chosen study arena.

1.6 Scope of the Study

The current study recognizes quality factors that are needed for the banking institutions to stay focused in the marketplace for ensuring their long-term existence, particularly in the age of fierce competition. Banking institutions may mitigate the possibility of transferability of current users to other institutions by implementing customer-focused service approaches based on the customer satisfaction metrics. Moreover, banking institutions can modify, restructure, or reuse the services they provide and customize them for meeting the end-users' demands through understanding of customer's expectations and experiences regarding to the banking service quality. In such way, the banks can ensure customer satisfaction and increase the number of users accessing their services and reduce the retention rate in the institutions. The users in this case examine service offerings from different businesses and choose those that offer higher quality services. The current study will help banks for the development of policies aimed at increasing the quality of banking services, particularly in scenarios where customer satisfaction is low and expectations differ significantly. The banking sector as a whole will improve due to their improved services that allows them to compare their strategies and policies for quality enhancement techniques.

1.7 Organisation of the Thesis

The current study is divided into five chapters. Chapter one is the introduction, where it provides the background about digital banking services, AI applications, etc., The problem statement, research objectives and questions, the need and scope for the study are also provided. Chapter two is the literature review, where it presents the comprehensive literature review of the study's various facets. It makes use of the research's industrial, academical, theoretical, and literary foundations. A review on the DB's effects on customer experience and operational efficiency are also provided. Chapter three is the research methodology, where it discusses the research design, research methods employed. Data collection and analysis techniques chosen is also discussed in this chapter. Chapter four presents the results, findings and discussions. Chapter five presents the conclusion, limitations and potential future directions.

Chapter 2: Literature Review

This research study was focused on analysing the impact of AI on customer experience when handling sensitive information and emotional encounters for financial services. The relationship between banking, technology, and customers has been analysed to organize the sections to provide in-depth discussion for customer trust. The literature studies about digital transformation have been reviewed relevant to banking, customer experience with digitalization, AI and self-service methods for financial services, and the perspective of millennials. The effectiveness of digital tools in determining customer preferences through localized dynamics and data analyses have been conducted in relevant to the Indian financial system and cultural aspects. The earlier research recommended that there is an evolution of users and technology with strong evidence and future research is required to focus on assessing the impacts of human-machine interaction on banking (Chugunova & Sele, 2020).

2.1 Customer Satisfaction with Banking Services

In recent days, technology has played a key role in the banking industry, where a positive relationship exists between customer satisfaction and technology usage (Li et al., 2021a). The study also disclosed that the banking sector should have to adopt an innovative approach to the provision of financial products and services to be competitive in the market. On the other hand, another study of Khan et al., (2022) sheds light on complexities associated with e-banking regarding customer satisfaction. The data findings showed that customer satisfaction is achieved in e-banking based on factors, such as convenience, accessibility, privacy, security, and speed. The research study of () discussed that the customers would be more satisfied with the financial services of foreign banks compared to the public and private banks (Kaur & Kiran, 2015). The influencing factors of customer satisfaction included appearance, fees and loans, and prompt service followed by bank accessibility, interest rates, and service availability which have shown less impact on customer satisfaction (Pakurar et al., 2019).

The customers' loyalty has been increased towards the banks which are providing internet banking services. The relationship between customers and the banking industry has been established with a good brand image that would improve customer loyalty (Riyadi, 2022). In addition, the study concluded that the loyalty of customers increased towards banks when they provided online Internet banking services to customers. Another research study of Kaura et al., (2015) remarked several factors that affect customer satisfaction in Indian banks, such as product attributes, bank tangibles, customer convenience, characteristics of employees, engagement with customers, and cost of transactions. The banks should have to adopt relationship marketing to attract new consumers and improve customer retention (Taleghani et al., 2011).

The research data findings showed that customer satisfaction was playing a significant role in e-banking in rural areas. The satisfaction of rural customers was quite satisfied with the digital banking services (Madavan & Vethirajan, 2020). The use of local languages would be encouraged to promote the e-banking channels in rural areas. Moreover, the banks should have to adopt the technology with fast-driven methodologies that could lead to customer satisfaction and trust (Hussain et al., 2023). The study evaluated the impact of customer service, technology convenience, information quality, security of technology, and technology reliability. The results showed that technology convenience has positively impacted customer satisfaction (Duarte et al., 2018). Relationship marketing is an important aspect in improving customer satisfaction in addition to competence, employee responsiveness, social responsibility, positive word-of-mouth, and reliability (Fatmawati & Faizen, 2021).

Another important dimension of customer satisfaction is the service quality in the banking industry. However, the service quality determinants, including empathy, tangibility, assurance, reliability, and responsiveness showed a positive relationship with consumers' satisfaction (Setiono & Hidayat, 2022). The data findings of the study showed that there is a positive relationship between customer perception and online banking (Tham et al., 2017). Therefore, the banking industry should have to focus on providing customer service quality in terms of empathy, tangibility, responsibility, and reliability.

2.2 Digital Transformation in the Banking Industry

The changes in business activities and processes have been demonstrated using the term known as digital transformation (DT). By comparing with other industries, banking companies had higher IT spending on average according to the reports (Buallay, 2020). Thus, one of the IT-intensive industries is considered as the financial services in which the digital technologies would be combined with the information, communication, computing, and connectivity technologies. Based on the social media channels, use of big data, and mobile revolution, the financial services have been transformed into digital services (Pazarbasioglu et al., 2020). Both value proposition of customers and daily operations need to be redesigned in the financial companies that leveraging digital technologies.

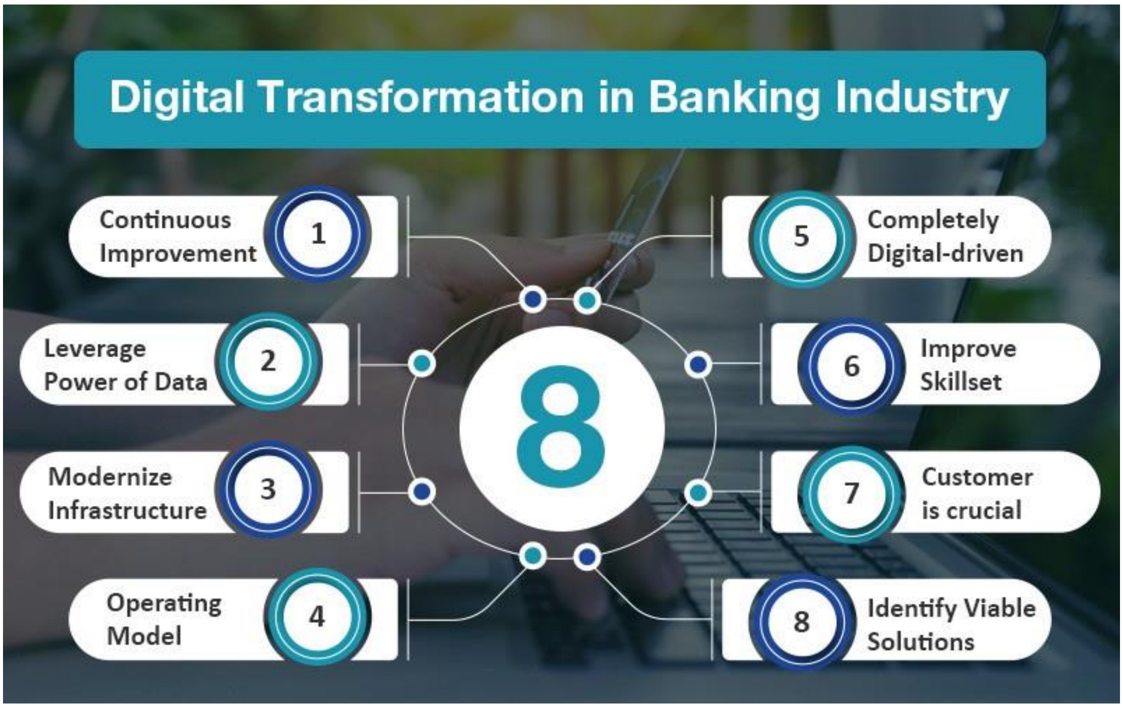

Figure 2.1: Digital Transformation in Banking Industry (Source: Cherinet, 2022)

The customers would be more attracted towards achieving net benefits since the innovation valued for service delivery and development. The customers' preferences and needs would be analysed in digital banking regarding the innovation of products and services (Figure 2.1) (Kaur et al., 2021). The metrics that would be quantified the return on digital investments while considering the self-service tools in the digitalization of financial institutions (Manser Payne et al., 2021). One of the major aspects is considered as the customer experience in digitally transformed banks. The customer experience has been improved with the implementation of digital trends which are automation and machine learning (Chakraborti et al., 2020).

2.3 AI-Powered Customer Experience in Digital Banking

Artificial Intelligence (AI) technology is demonstrated as the theory and development of computer systems to perform the tasks that require human intelligence, such as decision-making, speech recognition, and visual perception. The algorithms are combined with AI methods to imitate human intelligence with machines to emulate human behaviour. Several business processes have been integrated into AI where the data volume has exceeded the capacity of people to make decisions (Wamba-Taguimdje et al., 2020). Thus, the data analysis and determination of solutions for problems within a short period have been involved in AI technology.

The financial and banking industry is one of the economic sectors that could benefit from AI technology implementation. Fundamentally, the banking industry has been affected by AI in terms of optimized resources, operational efficiency, and gaining profitability based on the methodologies that integrate with information and technologies (Al-Surmi et al., 2022). However, the following aspects have been impacted by the AI-integrated systems in the financial and banking sectors.

The more accurate and faster evaluation of potential clients has been designed by using fewer resources only allowing the detection of risks in transactions through the personalized learning models. The significant advantages of using AI technology include automation, cost saving, risk management, and credit evaluation (Ashta & Herrmann, 2021). Thus, each bank or financial institution would make the financial planning efficiently using predictive models by adjusting multiple variables in real-time scenarios. The involved operational costs would be reduced in the financial operations. Thus, the banking industry can achieve efficient financial operations and reduce work stress by employing digital machines across different departments of business operations (George & George, 2023).

AI algorithms or methods can establish security mechanisms and schemes in all purchases by assessing consumer behaviour, purchasing habits, and user location (de Marcellis-Warin et al., 2022). It will assist in the monitoring of online transactions that would prevent fraud risks and money laundering. Suspicious financial operations can be detected through the recognition of data patterns that could prevent financial crimes in the banking industry. The monitoring benefits can also be provided by AI technology for designing intelligent investment systems to control unstructured data and structured data (Sarker, 2022). Thus, banking investors can manage solid portfolios with optimized resources and efforts.

The intelligence-based messaging robots provide new financial products and services that would facilitate personalized financial services, immediate solutions, and faster transactions and decision-making in personalized banking services. The most useful AI algorithms are machine learning (ML) models that would assist the banking industry in interacting with clients and solving instant problems with efficient communication (Agarwal et al., 2021).

The biases of AI-enabled systems are required to be considered in the banking and financial sectors. For instance, when evaluating the credit score using AI models, the discrimination of minority groups has been prevented (Sheth et al., 2022). The AI systems would be biased by human influence, evaluation or datasets although the technology is neutral. To reduce such effects, financial institutions have made many efforts like governance of data and careful selection when using AI models for reducing personal biases (Schwartz et al., 2022). The governments are taking action to maintain ethical safety and security. The Indian government has created legal frameworks regarding the ethics of AI to assist baking firms in developing and using AI responsibly (Chakrabarti & Sanyal, 2020). However, financial organizations can implement concrete actions using the legal frameworks in their business operations while addressing AI solutions responsibly.

2.3.1 AI-enabled Customer Experience

In the banking environment, the acceptance and adoption of digital banking services are considered a customer experience. The rapid responses will be demanded with custom-made content by customers when their predilections change between generations (Tulcanaza-Prieto et al., 2023). However, useful customer information can be addressed in the banking sector with the assistance of AI. It would be possible to assess the sentiments of customers and forecast their feelings or emotions and their interactions with the brand using surveys, social media interactions, and emails with the customers (Kubler et al., 2020). Qualified feedback on consumer sentiments would be provided using AI technologies that include machine learning and natural-language processing. The customer experience might be improved by retailers in the promotion of competitive advantages in the business firms (Keiningham et al., 2020). Accordingly, the customer experience will be improved and met their expectations.

The studies discussed four different aspects to integrate the customer experiences, such as physical and sensory contact (technology-related features, signage, clear design, and lighting), cognitive sense (speed, service availability, and functionality), emotional experience, and social factors (social and mental identity of customers) (Tulcanaza-Prieto et al., 2023). Based on available data, such as past experiences of consumers and their preferences, AI technologies would improve customer experiences that will increase consumer engagement and predict future tendencies (Bag et al., 2022). Therefore, the quality of customer experience might be increased with the interaction and integration of AI-enabled experience.

The hedonic utility with the strong self-relevant values of customers has been prioritized for customers. The acquisition experience based on sensations, emotions, and memory has been focused on hedonic consumption. Thus, a diminutive weight of rationality and consumption with hedonic characteristics have been interrelated with the emotions and ideas of customers.

However, a moderate or rigorous rational analysis of purchasing is not required for hedonic experiences that facilitate the relationship and decision-making process (Kazmi et al., 2021). In this context, the perception of individuals can be modelled using AI while purchasing financial products or services that give feedback or review of their experiences.

It is important to recognize the value of human contact which is the major limitation of AI implementation in the digital banking industry (Manser Payne, Peltier & Barger, 2021). However, the human touch cannot be replaceable with machines as it replicates the empathy, depth, and emotional connection. By understanding human movements and providing solutions, AI would become smart and build a meaningful relationship with the clients. AI-enabled customer experience could able to capture the client's perceptions through excellence in data collection and analysis (Puntoni et al., 2021).

Respect and gratitude for individuals or other businesses are shown in customer recognition. In business strategy, it is a powerful aspect that will assist financial corporations in maintaining customer loyalty and engagement. However, the qualities of customer recognition included importance, a sense of beauty, relation, and safety (Ameen et al., 2021). The competitive advantages would be transformed with the financial products and services including innovation factors in the digital banking industry. The purchase history of customers can be able to tracked by the brands using the advances in information technology, including AI that is linked to customer recognition (Kietzmann et al., 2018). It identifies new and repeated consumers based on their preferences. Thus, the financial and digital banking firms include innovative methodologies in the design of products and services with the trend of customer identification that intensifies the brand contest or marketing.

2.4 Possible Digitalization Methods for Efficiency Gains of Digital Banking Operations

The digital transformation was initiated in financial services that would develop detailed strategies in banking organizations to revamp the operation models, create an end-to-end customer-centric process, and improve customer offers. Digital transformation technologies could be embraced in the banking industry to generate value for banks and customers as well (Osei et al., 2023).

The necessary information would be provided for resolving customer issues through the leveraging of AI technology by online assistants and chatbots. Moreover, AI is used for data analysis, management, security, and improving customer experience (Daqar & Smoudy, 2019). The repetitive patterns can be recognized using AI with the analysis of consumer data within seconds. The machine learning model has a potential advantage for digital banks to collect, store, and compare user data in real time (Munappy et al., 2019). Fraud detection is another significant advantage of using ML models in the banking sector that could detect changes in user actions and take preventive measures using machine learning.

2.4.1 Efficiency Gains of Digital Transformation

The transformation of digital banking is more than online banking and instant online transactions. It would bring a lot of new opportunities for large financial institutions and small and medium businesses. The following benefits would be provided with the digital banking transformation.

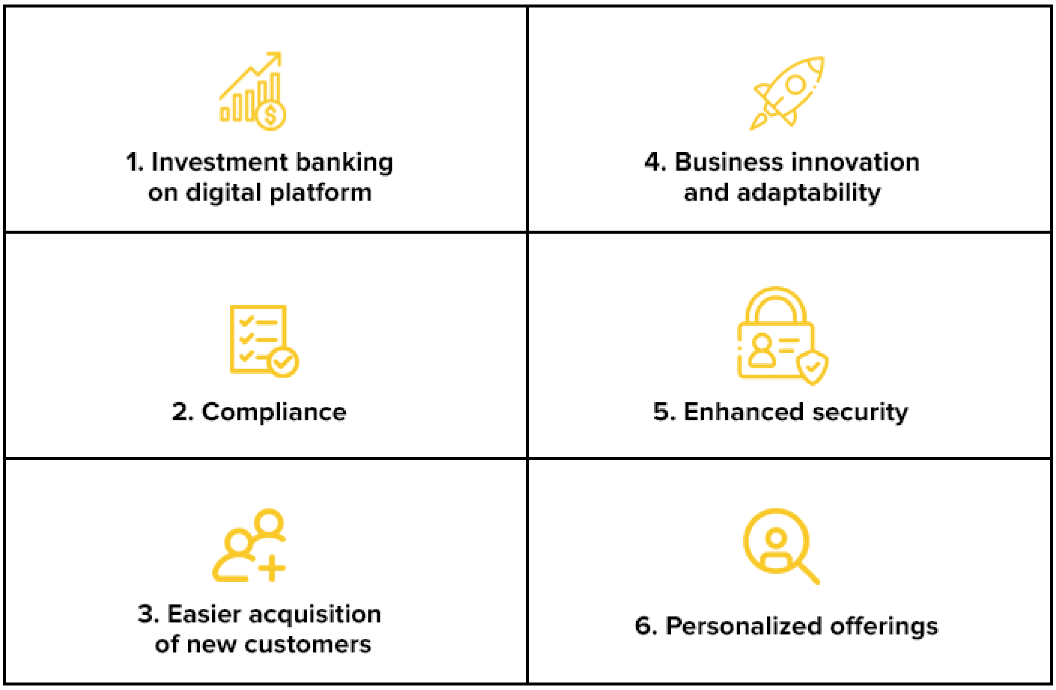

Figure 2.2: Efficiency Gains of Digital Transformation in Banking Industry (Source: Singh, 2024)

The reduced intermediate processes and data transparency can be maintained with the expansion of digital banking in accessing intellectual data. The operation costs can be impacted positively by these factors which would make easier and faster transactions (Singh, 2024). The investment banks were replaced with small investors through the digitalization of banking to focus more on short-term goals (Figure 2.2). Thus, investments in technology would assist digital businesses or enterprises in fulfilling customer requirements immediately.

To be compliant with the modern digital financial management systems in banking sectors, advanced features like auto auditing would help the employees spend less time on auditing processes. The AI-enabled digital banking stays standardized and can be shared on multiple platforms without any financial errors (Theuri & Olukuru, 2022). The digital payroll system can provide timely updates using AI technology which means the banking industry need not worry about the regulations.

It becomes an easier and cheaper way to attract new consumers for banks and every other sector as financial corporations are not passive about their financial services. Every business and consumer should operate their operations hassle-free with instant online payment. However, banks and other financial institutions have been reaching their consumers easily with the emergence of online portals, social channels, and mobile banking applications (Shareef et al., 2018). Thus, new business innovations have been achieved with the digitalization of the banking industry which is reliable and highly dependent on banking services. Currently, financial institutions have been struggling to overcome issues like customer data security. The sophisticated software development services have protected sensitive data and saved customer bank accounts from scamming activities in the digital banking sector (Achar, 2018).

The banks would be allowed to make digital transformations in providing financial services according to consumer needs. The financial institutions have initiated the designing of innovative products and services based on the daily expenses of customers which would be the greatest advantage of digital banking to its users (Chen et al., 2017). More businesses and organizations have adopted the solutions and services of digital transformation for better opportunities.

Advanced digital technologies like AI have gained a competitive advantage for the banking sector through the leveraging of digital transformation solutions. However, complete control over end-to-end financial operations can be gained in financial corporations in addition to usability and consistency. The mobile applications can allow individuals to access financial data, bank accessibility, and financial management with customised solutions (Bhatt, 2021).

Furthermore, deriving the greatest value from the business data is the crucial aspect of achieving business success. Thus, data analytics solutions and services based on AI technology would assist the banking sector in transforming data into valuable insights since they deal with massive amounts of data from multiple sources relevant to customers (Akter et al., 2022).

2.5 Millennials' Perspective and Customer Trust

The millennials were considered as individuals who were born between 1980 and 2000 in this research study. In comparison with older generations, the millennials have higher debt levels. Their trust or loyalty for any type of financial firm has been achieved based on their level of satisfaction, accessing the services, and purchasing of products. The quantitative study showed that millennials prefer mobile banking over online banking which is a unique characteristic of this generation. The millennials are targeted by smaller banks as challengers who are likely to become 75% of the workforce by 2025, and small to medium-sized businesses (Karahanli & Touma, 2021). Thus, the use of modern technologies would gain much importance in the innovation and differentiation of products.

The studies demonstrated that 44% of millennials have used at least one type of loan or advance and 25% indicated a lack of financial knowledge (Lusardi, 2019). The gamification applications would improve the debt repayment behaviour of customers while delivering the required education and training for them through the gamification applications. When considering their ignorance and lack of knowledge in making payments, it is argued whether the customers' consciousness or awareness would be profitable for digital banks or not (Mogaji et al., 2021). In this case, the technological advancements would create new values in digital banking. The machine learning methods would be useful in determining the bias or risks towards certain genders or races to restrict the banks that are required to train their developers for data protection and equality (Mehrabi et al., 2021). Customer engagement and trust should become important aspects for any digital banking firm when building sustainable relationships.

Chapter 3: Methodology

The cluster analysis was carried out for the customer dataset to identify the distinct groups among customers. However, the customer dataset of the Indian banking sector was obtained from Kaggle and comprised 1048567 observations with different attributes, including transaction ID, customer ID, DOB, gender, location, account balance, transaction date, transaction time, and transaction amount. Some pre-processing steps are required for clustering owing to the associated dimensionality curse and unstructured nature of customer data. A research approach was presented to perform the holistic consideration for cluster variant application that reflects the methodological and procedural implementation of the research objectives.

To perform the efficient clustering method, a prepared database should be available for including the maximum information content for a systematic structuring of unstructured data based on clustering methods. Before conducting the active clustering implementation, some pre-processing methods are required to be performed for achieving the structured customer dataset and cleaned data.

3.1 Dimensionality Reduction

The curse of dimensionality resulted in the quantification of the natural language processing. It would be a significant challenge for the data pre-processing step to perform the clustering methods. The underlying indicators and data with reduced dimensional data can be reproduced by evaluating the dimensional expansion extensively based on various reduction algorithms iteratively (Jia et al., 2022). The feature selection (FS), feature extraction (FE) methods, and a statistical approach were used for the reduction of dimensionality. The machine learning techniques were used in FS and FE to carry out the dimensionality reduction while determining the correlating dimension terms statistically (Zebari et al., 2020).

According to Khalid et al., (2014), dimensions were chosen from a set of features in FS that contribute to the performance of an ML model significantly. However, an empty set is initiated with the forward selection in the FS method that adds the relevant dimensions gradually to the set of chosen dimensions until achieving the increased performance (Shen & Zhang, 2022). In the backward selection process, the entire set of attributes is initiated and removed those successively causing the reduced performance until there was no increment in performance (Nguyen et al., 2014). The local optimum problems have been faced by both approaches. To overcome this issue, the optimize selection (OS) method was used based on a greedy algorithm to approximate the local optima. On the contrary, optimized selection attributes are not included in FE, but new dimensions can be extracted by integrating the existing dimensions systematically. Thus, novel composite dimensions are represented based on multiple features (Zebari et al., 2020). Based on orthogonal transformations and linear combinations, the dimensions can be reduced to a set of factors for converting the correlated attributes to non-correlated attributes in the principal component analysis (PCA) (Machlev et al., 2020). This study used the dimensionality reduction of PCA to implement the procedural milestones efficiently.

3.2 Determining the Optimal Cluster Number

It was required to evaluate the optimal cluster number ‘k’ before applying the clustering procedure. This step was necessary to determine the predefined number of clusters that would be used as input for chosen clustering techniques. In addition, important insights for clustering methods are also provided based on number of clusters. Depending on the chosen approach of clustering, the clusters can be evaluated in the first pre-evaluation. Then, the methods of elbow plot that consider the average centroid distance, the Silhouette index, and the sequential evaluation of the Davies Bouldin index were compared to determine the clusters' number k accurately for consumer data interpretation (Wilbert et al., 2023).

The smallest value of k has been chosen in the heuristic elbow techniques based on the generated scree plot. Here, a strong transition exists at the transition to the previous k-value when distortion starts to increase sharply. The number of clusters was chosen in such a way that the addition of another cluster would not provide accurate data modelling for the underlying customer dataset (Sagala & Gunawan, 2022). The average within the centroid distance was taken as a criterion when generating the elbow point. Thus, the clusters have been represented numerically in this way.

To complement the optimal cluster number, the Davies Bouldin (DB) index was utilized to determine the optimal number of clusters k. According to the predefined k interval, the DB index was determined iteratively. However, the corresponding DB value was determined for each cluster number k (Ashari et al., 2022). By considering the relationship between the distance between clusters and within each cluster, the DB index was calculated more precisely. Therefore, the lowest DB index was represented as the optimal number of clusters that were chosen based on the maximized distance between clusters and minimized distance within the clusters.

The Silhouette index is represented as an approach for optimal cluster number k. It is a more complex method when considering the running time. More information about the quality of cluster number k was provided using the Silhouette index by comparing it with the elbow method and DB index. Thus, it would have been utilized as an additional complement (Hassan et al., 2021). The clusters with a positive coefficient and closer to 1 that their data points were distant from the neighbouring cluster. Thus, the cluster splits are preferred and the threshold range of the decision between two clusters is very close for clusters with a coefficient of zero. The data points were allocated wrongly in the negative coefficients and corresponding clusters showed the outliers. The negative coefficients of clusters were avoided although the cluster groups could not always determine precisely in the higher dimensional space. Similar to the DB index, the Silhouette coefficient was determined in this study for the customer dataset of each k in the given interval based on the determination of clustering performance which was calculated using the difference between clusters and within the clusters through the pairwise distance (Punhani et al., 2022). The study of Amrulloh et al., (2022) showed that the Silhouette index was chosen as the maximum value of the Silhouette and the minimum value of the evaluation chain was chosen for the DB index. Thus, these three approaches provided the optimal cluster number and were used in the pre-evaluation of the number of clusters and implementation of the clustering methods in this research study.

3.3 Clustering Techniques

A predefined cluster number k was required for some clustering methods while some other clustering methods have determined the number of clusters through internal evaluation. In the research study, the clustering methods need to be usable for the dataset. However, three different clustering methods were chosen and evaluated in our research study in terms of performance metrics. They included k-means, hierarchical agglomerative clustering, and DBSCAN methods (Cahapin et al., 2023).

The widely used method is considered the k-Means clustering method in different real-world scenarios. This method can be computationally efficient specifically for high-dimensional data by considering the cosine similarity. The individual instances have been allocated to the cluster with the closest centre of the cluster in the k-Means clustering that categorises the underlying dataset into a predefined number of clusters (Mousavi et al., 2020). A lower overall distance to the cluster instance can be found as a cluster centre than the current centre and its convergence criterion is fulfilled.

The clustering method of DBSCAN was better able to differentiate the clusters of a dataset through the minimum density level of the dataset compared with other clustering methods. A cluster is formed in the same high-density area in the data points and separated into different clusters based on low-density areas with few instances only (Bushra & Yi, 2021). The minimum number of points in the neighbourhood and the radius eps of the neighbourhood are defined in this method to determine the areas. Subsequently, these parameters are used for the clustering method iteratively for the expansion of clustering groups. The clusters were allowed to be found in arbitrary shapes and low-density areas included the outliers in DBSCAN.

This research study evaluated the hierarchical agglomerative clustering which would enable building the relationships between sub-groups and super-groups of clusters by pre-defining the number of clusters based on the interpretation of the dendrogram. The visualization of the cluster divisions is presented in the dendrogram which enables to determination of the optimal cluster number. Most neighbouring pairs of clusters have been merged in the agglomerative hierarchical clustering methods to form the clusters (Zhou et al., 2016). Our research implemented different clustering approaches and needs to be analysed for high-dimensional customer data in digital banking.

3.4 Performance Evaluation

The quality of determined cluster groups was evaluated in the last phase of the research approach through the performance evaluation. In this step, how well the data is represented in the cluster groups or how well the partitioning of clusters was performed based on the implementation of methods were examined. However, the evaluation of performance was a significant challenge in the dataset, thus, it required to be optimized to determine the optimal cluster number and apply the clustering methods. This was carried out until the splitting of clusters could be found which facilitates the better values of performance evaluation. The internal evaluation metrics were used from the optimization of clusters k to analyse the clusters to ensure a holistic perspective and facilitate the cluster quality with a clear assessment (Li et al., 2021b). Based on the internal cluster information, the internal evaluation criteria were characterized while comparing the results of clustering methods. These measures of performance evaluation can determine to what extent the prediction methods could be able to forecast the same cluster labels. Thus, the complementary data can be derived about the quality of clusters.

This research approach used two internal evaluation criteria. However, the noise points and Silhouette index were determined for evaluating the performance of performed clustering methods (Murugesan et al., 2021). They were considered as internal evaluation parameters for the final cluster groups.

In summary, the underlying customer data of the digital banking industry was processed step by step based on the objectives of the research approach. They included the evaluation of an optimal number of clusters based on different optimization approaches, determining the potential of clustering methods that could be implemented for customer datasets, and measuring the performance of implemented clustering approaches (Li et al., 2021b). These steps were performed to evaluate the best cluster distribution with a holistic view based on different perspectives.

Chapter 4: Results

This section demonstrated the AI-driven trust and personalization model in digital bank financing based on customer account balance and transaction amount. It is difficult to investigate the interplay between bank customer account balance, transaction amount, personalization, and trust. Both assessment of credits and risk mitigation have been influenced by personalization. As a result, the customer's financial behaviour can be impacted by the customer's trust in the banks that lower credit risk. Through personalization and effective data practices, customer trust should be established in digital banking. In this context, the important points needed to be considered. Customer satisfaction needs to be achieved by fulfilling their financial obligations while consumer trust plays a key role in digital financing. Banks and financial institutions need to maintain transparency with customer transactions to ensure trust. In digital banking, personalization is considered according to the data collection and analysis to facilitate the services for individual customers. For instance, banks might have utilized personalization or customization to provide customers with unique interest rates, credit limits, and lending possibilities. With the AI integration of digital banking, efficiency gains in terms of risk assessment and mitigation can be achieved that can provide personalized financial services to customers. The confidence between banks and customers can be fostered with the establishment of trust through personalization. According to the financial situation and demands of customers, banks can provide customized financial services that will ensure customer trust. The personalization and trust factors have been associated with data privacy and security. Customers should have trust in digital banks that their financial data will be treated with care and security. Increasing trust is another way to reduce the risks relevant to credit because the customers will feel trustworthy and equitable and maintain good credit behaviour. By considering all these points, the architectural framework was designed for this study.

4.1 Architectural Framework

As shown in Figure 4.1, the architectural framework was designed based on Natural Language Processing (NLP) models in machine learning (ML) that linked to the learning algorithms to examine data for classification. The diagrammatic representation of the designed framework is shown in Figure 4.1. Two different sections are included in the architecture, such as data preprocessing and classification. However, the raw dataset of Customer Transactions and Account Balance was considered and fed into the data preprocessor in which the data was converted into numerical data followed by normalization of scaling the values between 0 and 1. The normalized data was evaluated for feature extraction based on exploratory data analysis (EDA). Then, the outcomes were fed into the NLP (Natural Language Processing) classifier to detect the transaction (1) or no transaction (0). Three different algorithms were used in the NLP classifier, such as K-means clustering, hierarchical clustering, and density-based spatial clustering with applications with noise (DBSCAN) to determine the efficiency of the model in detecting the impact of AI-based personalization on customer satisfaction and trust in terms of increased transactions.

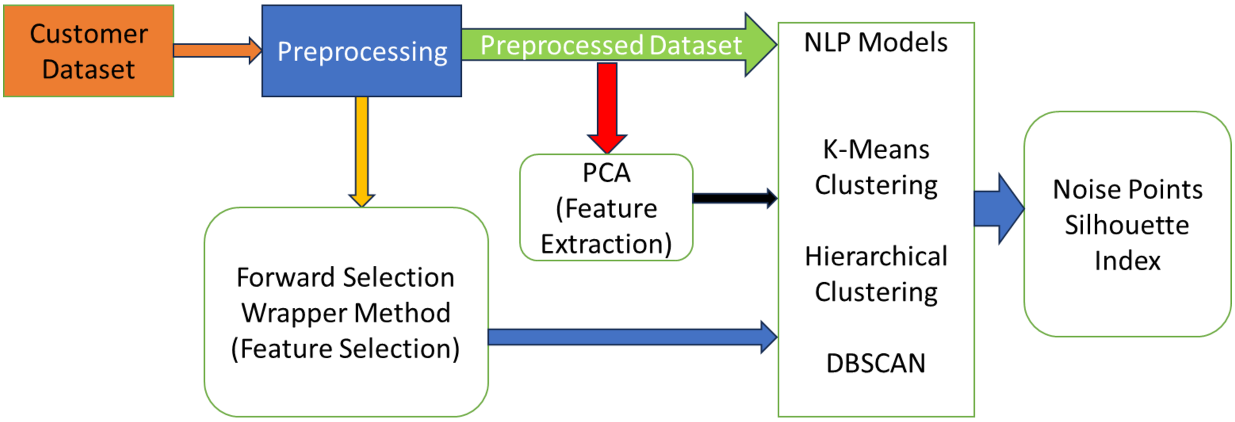

Figure 4.1: Architectural Framework of Research Study

4.2 Exploratory Data Analysis

Different performance indicators were used in the data analysis of the chosen dataset in Python, such as heat maps, box plots, pair plots, correlation matrices, and distribution plots for accessing the characteristics of the extracted features. However, the heat map and correlation matrix of the features against the target variable of customer gender (0- Female; 1- Male) in the initial feature extraction (Figure 4.2). The features with correlation >±0.1 were included whereas the features with correlation <±0.1 were dropped from the analysis. Several features (F1, F2, F3, F4, F5, and F6) were included at this stage.

Figure 4.2: Heatmap of Features with Target Variable of Customer Gender

Then, the characteristics of the features were examined through the principal component analysis (PCA). The characteristics of features like customer account balance, transaction amount, transaction amount, age, transaction day, and transaction month were evaluated to reduce the number of features in the dataset while preserving the most important information like major patterns. However, this reduction reduced the time required for training the machine learning models and assisted in avoiding the model overfitting. This study used pair plots for data reliability and determining the distribution of numerical data and skewness (Figure 4.3). By observing the features in the pair plots, it was observed that the features customer location, transaction time, transaction month, transaction day, and age had a few shortcomings, such as unbalanced data type, unbalanced density peaks at target 0 and target 1, and lower magnitudes.

Therefore, these features were dropped in the data analysis and two features (F2 and F4) of customer account balance and transaction amount were included for better classification of features.

Figure 4.3: Pair Plot for Features with Target variable of Customer Gender

4.3 Analysis of Natural Language Processing (NLP) Model

The environment was established for the classification of the final extracted features (F2 and F4) in Python for data analysis. Three types of unsupervised NLP classifiers K-means clustering, hierarchical clustering, and density-based spatial clustering with applications with noise (DBSCAN) were used to perform the classification of features.

The k-means clustering was used to perform the clustering of a dataset of customer transaction data collected from Indian retail stores. Upon data pre-processing, the customer transaction data was determined that greater than two clusters would have to be considered in the cluster generation. Based on this, the customer account balance and transaction amount were examined for further evaluation of k-means clustering. The determination approaches like the elbow method, Silhouette score, and Davies Bouldin score were used to find out the optimal number of clusters. It should be noted that the optimization methods can provide the optimal number of clusters only. Thus, the results were evaluated holistically regarding the proposed research questions relevant to AI integration and personalization for consumer trust and satisfaction.

4.3.1 k-Means Clustering

To propose an optimal number of clusters, an elbow point was determined for the underlying dataset in the elbow method. Figure 4.4 shows that it was given that 4 to 8 clusters could be considered as an optimal number of clusters in this particular case by examining the dataset. The interval range for a k of [4;8] was enabled and considered the optimal number of k with a higher probability concerning the higher dimensional space. Therefore, other remaining methods were also evaluated for an optimal number of clusters for a clear selection.

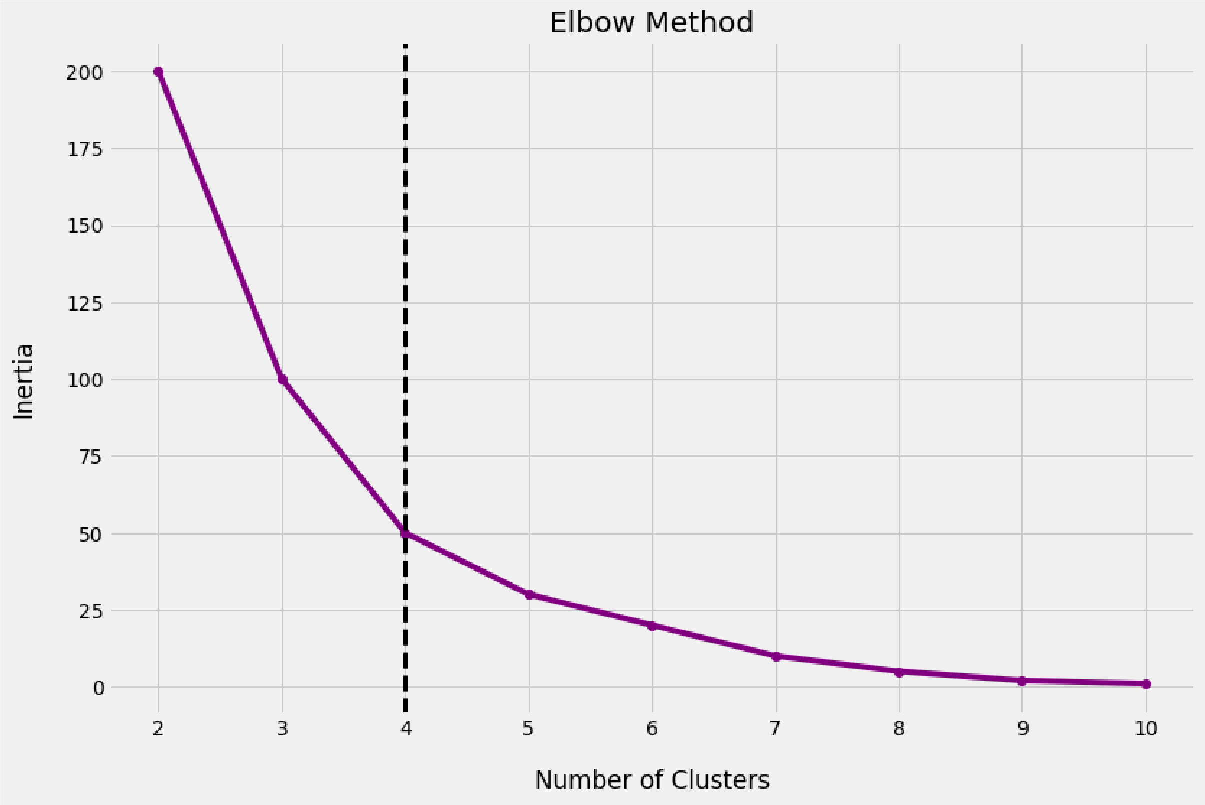

Figure 4.4: Elbow Method for Determination of Optimal Number of Clusters based on Feature Selected Dataset

The DB index was evaluated iteratively for the dataset as a second optimization procedure. However, the optimal number of clusters was considered as the minimized DB index. Based on the obtained results, the DB index tended to reduce with the increasing k after some highs and lows. The lowest point before the high slope was considered as an optimal cluster number and used as an approximate value. Since the slope of DB fell steadily up to a k of 5, the indicators referred to the cluster number as five for our dataset. However, the largest rebound was noted for the DB slopes from a k>5 (Figure 4.5).

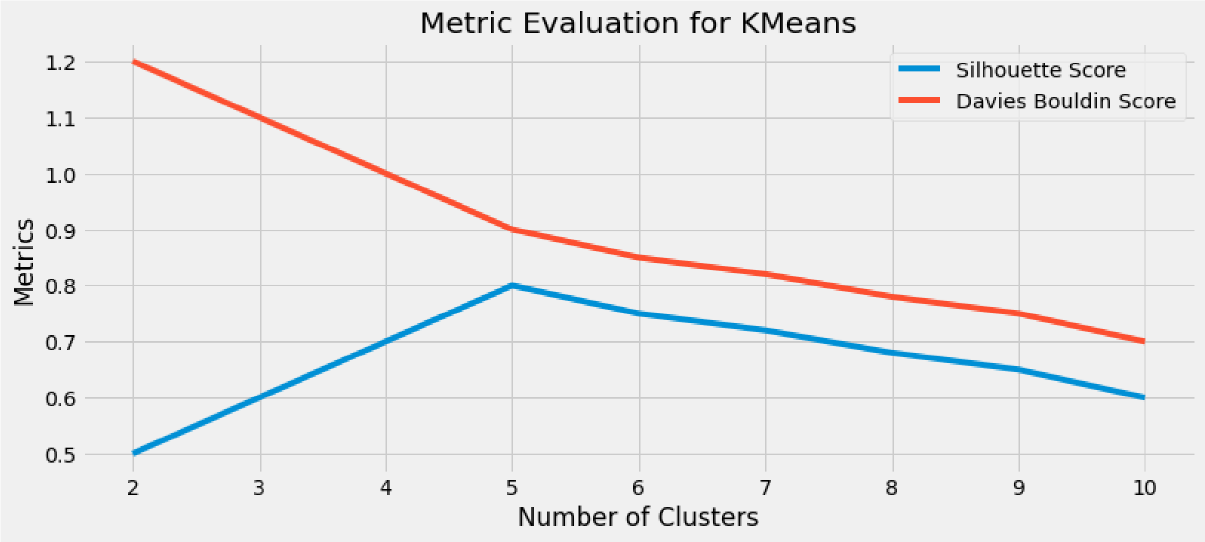

Figure 4.5: Davies Bouldin and Silhouette Evaluation for Feature Selected Dataset

Consequently, the Silhouette index was also evaluated for the precision of several clusters k for the underlying dataset. The optimal number of clusters has been chosen when the Silhouette score is maximized with the increasing k-value. As shown in Figure 4.5, the curve gradually increased before reaching its maximum at a k-value of 5 and dropped subsequently. Thus, a value of 5 can be taken as the optimal proposal for the dataset.

In summary, all derived indicators of all optimization methods have indicated a cluster splitting recommendation of k = 4 to 8 for the Elbow method and k = 5 for both Davies Bouldin and Silhouette scores for the feature selected dataset. In the first step of the clustering, a k-means approach was used as k = 10 which was considered after fitting the model.

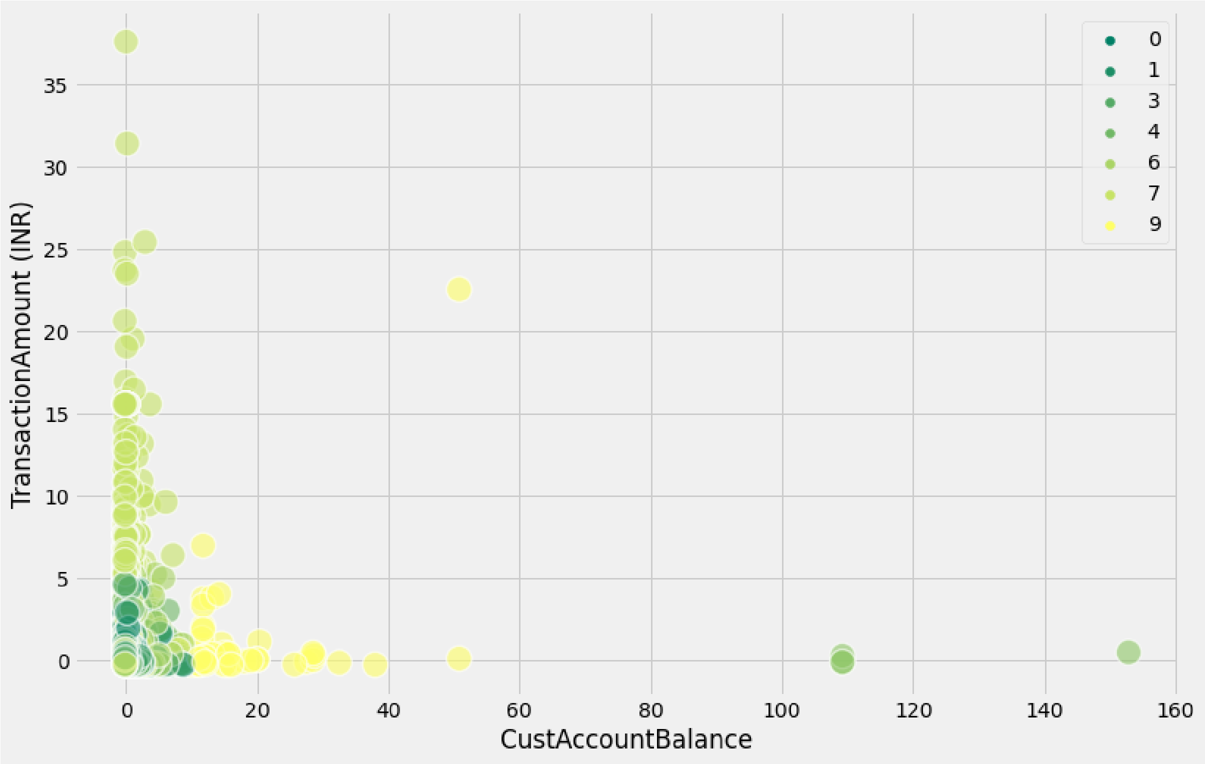

Figure 4.6: Cluster Partitioning for K-means Clustering

The information regarding the proposed optimal number of clusters was required for the k-Means approach in the first step of the clustering. However, k=10 was chosen for the dataset and cluster distributions were presented in Figure 4.6. On average, the same number of data objects are included in the cluster group from k = 0 to k = 7.

4.3.2 DBSCAN Clustering

The density-based approach, known as DBSCAN clustering was used to determine the cluster distribution for the dataset. The dataset was clustered using DBSCAN and showed the result for seven clusters in contrast with the k-means clustering. It indicates that enough dense regions were there in the data for the identification of multiple clusters. This could be the result owing to different parameters like distance measure, choice of density parameter, or data quality. The clusters may provide sufficient data to determine the influencing factors of customer trust (Figure 4.7). This resulted because the clusters were based on the transaction amount and available account balance of customers.

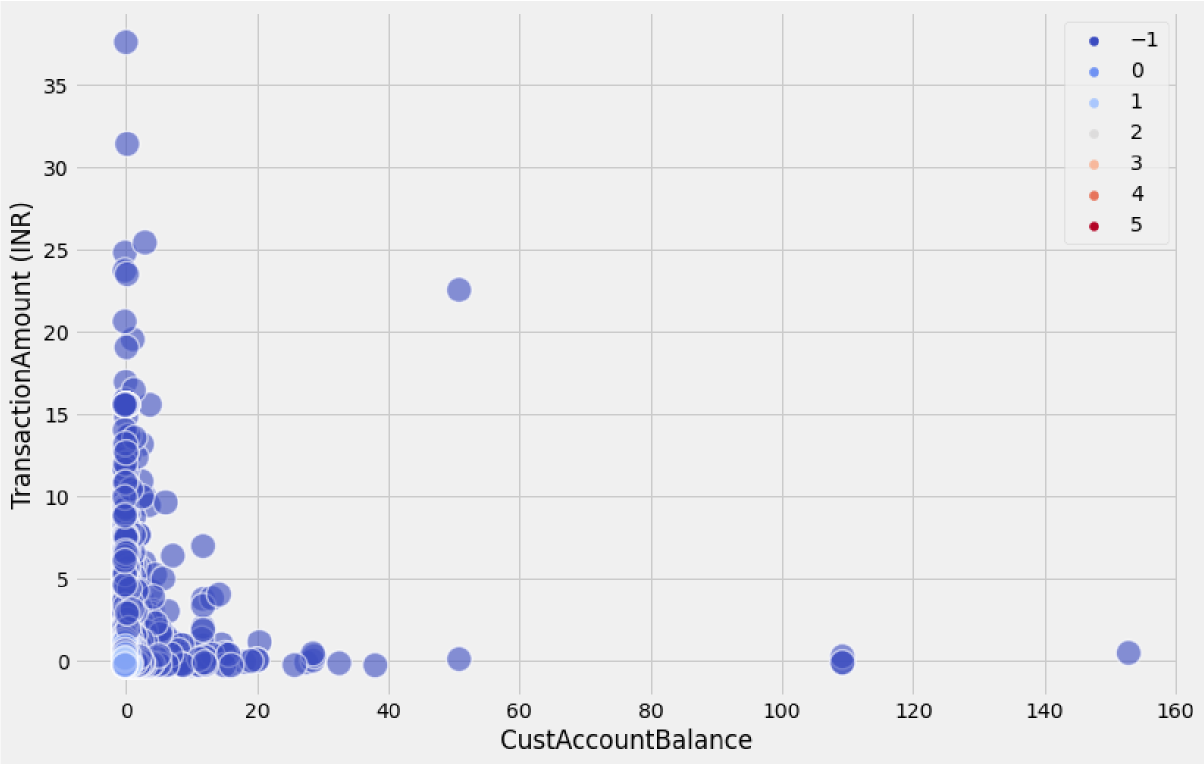

Figure 4.7: Cluster Partitioning of DBSCAN Clustering

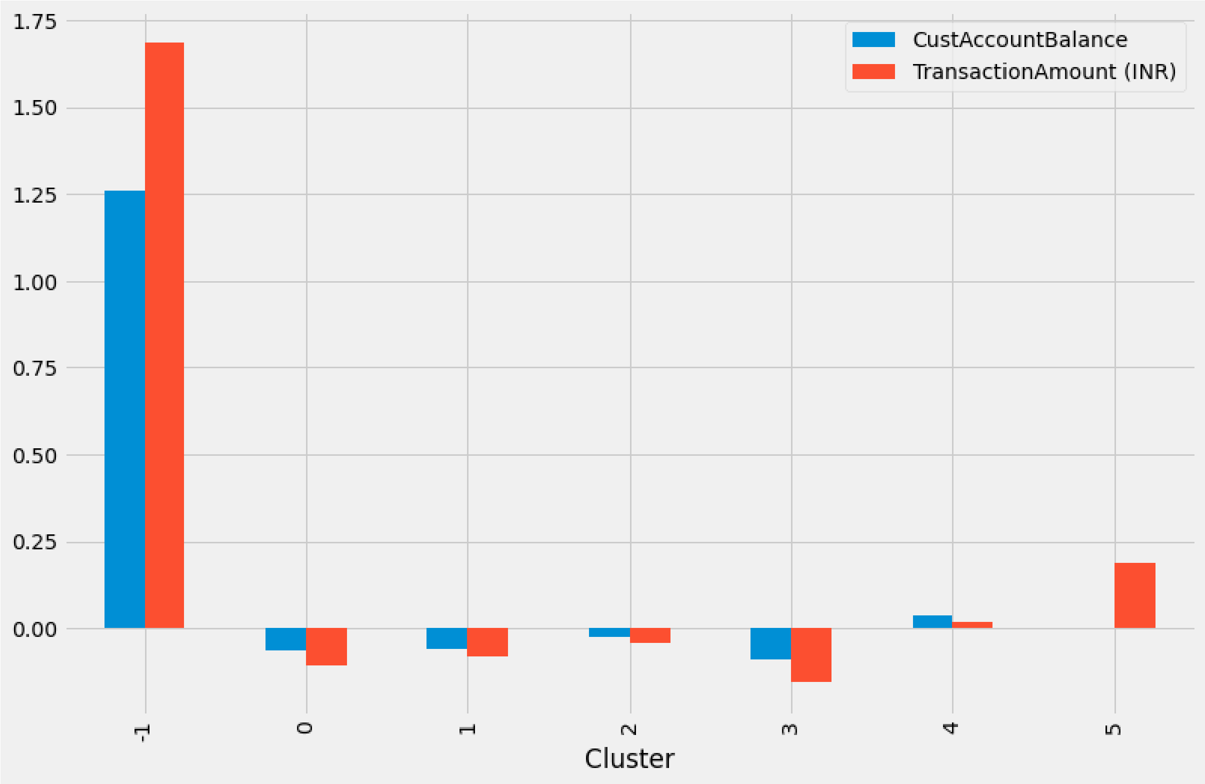

Figure 4.8: DBSCAN Clustering for Customer Account Balance and Transaction Amount

After performing DBSCAN clustering for the dataset, only one cluster showed the dense region for both customer account balance and transaction amount (Figure 4.8).

4.3.3 Hierarchical Agglomerative Clustering

The hierarchical agglomerative clustering was implemented based on the high-dimensional data. The usable results could not be derived for this dataset because of the included higher number of underlying dimensions. Moreover, the cluster distribution was not performed due to the dense distribution of the hierarchical arrangements. A total of 22 cluster partitions could be determined. Upon checking the average of all intersections between the respective partitions for the purpose, only two clusters had dense regions in the data relevant to the transaction amount and customer account balance (Figure 4.9).

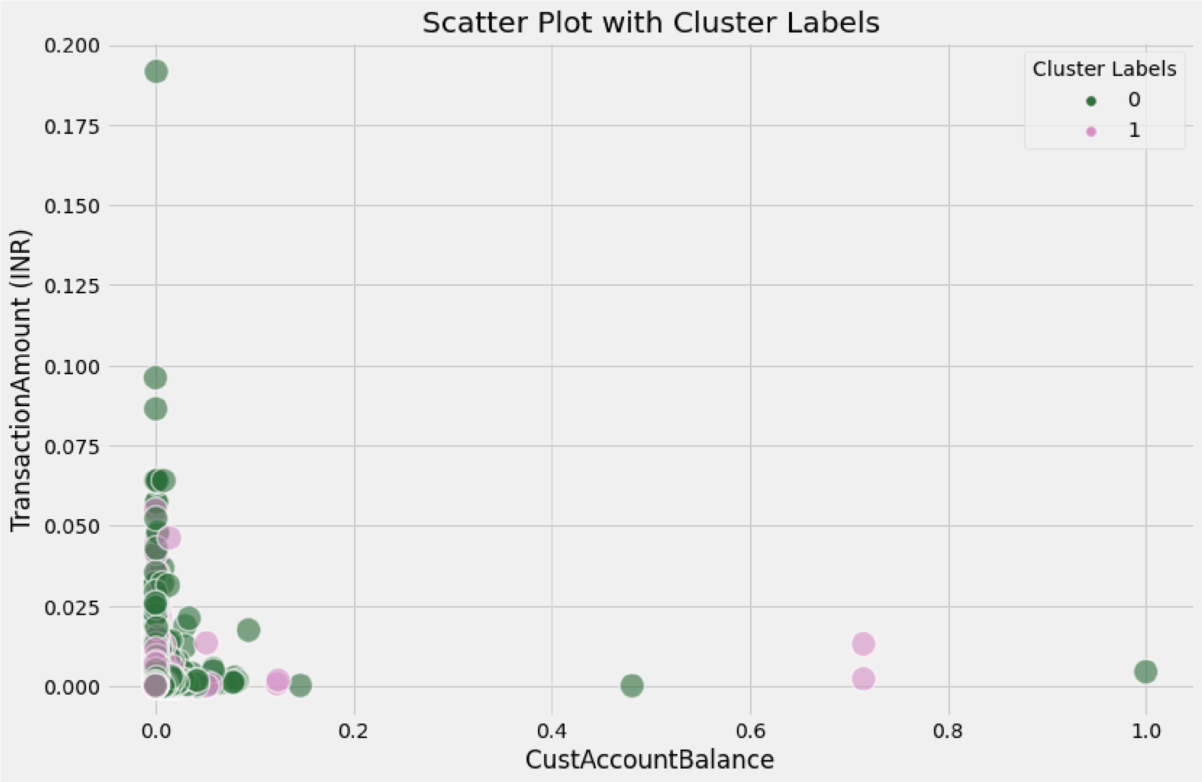

Figure 4.9: Clustering of Hierarchical Agglomerative Clustering

Three different cluster separations were evaluated during the clustering process. Still, it was unclear which results represented the best division. Thus, the next step is considered to evaluate the performance evaluation metrics based on several noise points and the Silhouette index for the dataset presented in Figure 4.10.

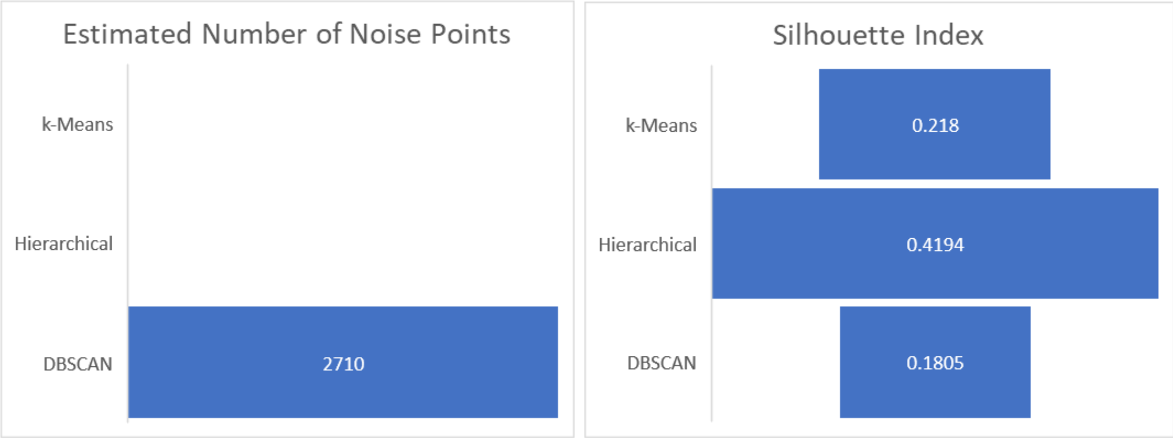

Figure 4.10: Performance Evaluation of k-Means, Hierarchical Agglomerative, and DBSCAN Clustering in terms of Noise Points and Silhouette Index

Starting with the estimated number of noise points, the minimum value was chosen as the best. As shown in Figure 4.10, both k-Means and hierarchical agglomerative algorithms showed the minimum value of zero while DBSCAN resulted in the highest noise points of 2710. Therefore, k-Means (k=10) and hierarchical agglomerative (k=2) models provided the best results in the minimum noise points.

In the case of the Silhouette index, the highest value would be considered the best one. Consequently, DBSCAN resulted in the worse Silhouette index (k=7) with 0.1805 compared to the k-Means (k=10) with 0.218 and hierarchical agglomerative (k=2) with 0.4194. therefore, the best Silhouette index of 0.4194 was achieved with a hierarchical agglomerative method than the k-Means and DBSCAN. Overall, it can be noted that the hierarchical agglomerative outperformed the best cluster separation for the minimum noise points and Silhouette index when considering the internal performance evaluation metrics.

It is still a good idea to use clustering as a decision-support tool to optimize the customer experience and trust in digital banking. As shown in the results, clustering could be a useful technique to detect the similarities and patterns in large datasets of digital banking that could be used to make informed decisions about efficiency gains and consumer trust. Digital banking institutions need to consider incorporating the other influencing factors of customer trust and data sources like survey findings relevant to customer satisfaction and trust into the clustering to ensure the clustering results would be practical and meaningful. From the above data findings, digital banks can consider customer account balance and transaction amount factors to determine customer trust and efficiency gains in the AI-personalized customer experience using hierarchical agglomerative clustering.

Chapter 5: Discussion

Advanced AI technologies have been implemented in the banking industry across financial operations lowering operating costs and improving banking services. This study was focused on evaluating the impact of AI-powered personalization in digital banking in terms of customer experience and customer trust in the Indian banking environment. However, the results depicted the strength of customer satisfaction and trust factors associated with the AI-enabled customer experience in the banking industry, including financial technologies with AI algorithms in their services and products. It was determined that the integration of AI personalized features in the banks with options to make transactions, access financial suggestions, and check their balances would provide customer satisfaction since they provided improved scores. In this case, the digital banks measure factors like customer satisfaction and trust which are considered as the key factors of AI-enabled customer experience that would provide the scores for a financial service or product in terms of their needs, expectations, and facilities.

5.1 Impact of AI-powered Personalization on Customer Satisfaction

This study validated that efficiency gains, customer satisfaction, and trust have been influenced by the AI-enabled customer experience in the Indian banking environment. The data findings of improved clustering of customer experiences with hierarchical agglomerative clustering method in natural language processing (NLP) technologies should be utilized in customer support to engage them and monitor their relationships with digital banks. It is crucial to establish customer trust and achieve customer satisfaction by providing personalized customer experiences for online consumers with the continued digital transition (Demirel, 2022). Specifically, product suggestions are an excellent choice for personalized customer experiences as they assist consumers in discovering financial products that are suitable for their interests and preferences. The decision-making tasks have been streamlined with the implementation of AI in digital banks to improve the efficiency and effectiveness of financial operations (Agarwal et al., 2021). As our study showed that NLP-based hierarchical agglomerative clustering was efficient enough in monitoring customer transactions, digital banks can enhance customer trust and achieve customer satisfaction with the improved efficiency and effectiveness of financial operations. Moreover, the AI-enabled customer experience can increase the profitability of digital banks. Furthermore, banking firms would become competitive with the integration of AI data processing technologies offering a promising future for financial institutions (Tulcanaza-Prieto et al., 2023). These developments would change how consumers interact with the banks, how they purchase products, access services, and much more. Thus, the AI-enabled customer experience would have the potential to understand the sophisticated customer needs and make the customers more loyal to the digital banks.

5.2 Influencing Factors of Customer Trust in AI-enhanced Digital Banking

Customer trust can be increased with the adoption of AI in the digital banking industry. Privacy dilemmas have been faced by some clients as a result of personalization and digital banks should strike the balance for the personal data of consumers. The value of reaching closer to their consumers has been discovered by digital banks and providing suggestions to provide customers' trust (Kaur et al., 2021). In this research study, the data findings support the arguments that customer personalization and satisfaction are nested into customer needs in terms of online transactions and account balance. The data findings are important because they could to address the customer needs and satisfaction in Indian banking companies which would have a positive impact on AI-enabled customer experience. A better AI-assisted and AI-enabled customer experience may increase with the higher customer satisfaction and trust. The customer perception relevant to personalization, satisfaction, and trust have been fulfilled with the AI-enabled experience in digital banking environments that would assist in achieving the competitive advantage (Tulcanzao-Prieto et al., 2023).

The information and experience of the customers are considered in the implementation method of data findings in the digital banking industry. The perceived factors like customer account balance and transactions were evident that they impact on the customer satisfaction and trust in the digital financial institutions. This indicated that the banking organizations have to understand the needs and preferences of consumers based on the assessment of clients' data to support the user queries and design the personalized customer services in real-time. Thus, the digital banking industry is required to analyse the privacy and security of consumer data while incorporating the AI-training models for relevant data and designing the AI platform to provide a convenient and efficient user experience in digital banking services. The similar studies have been developed in the Asian, American, and European countries (Manser Payne et al., 2021). This study showed the new insights into the banking sector that can be used for creating the improved user experience by implementing the AI technology in bank services and achieving the competitive advantage. The integrated AI has been changed the digital banking dynamics while retaining the AI-enabled customer experience and increasing the customer loyalty. Therefore, it should always require to find new avenues for digital banking industry to enhance the customer experience and satisfaction based on AI technologies.

The major benefits and drawbacks of AI are included in the customer experience for digital banking industry. The advantages are personalized messages and content based on AI algorithms that could enable the delivery of personalized content, reduced costs with the real-time customer engagement, and facilitating the personalized and data-driven customer experience over competitors (Chaitanya et al., 2023). On the other hand, the drawbacks of AI-enabled customer experience included the wrong decision-making when data cleaning is not included, loss of human touch as consumers want to interacting with humans, and cyberattacks (Tulcanazo-Prieto et al., 2023). This study investigated the results of Indian digital banking industry that would recommend the following design and implementation along with practical ways of implementing the AI technologies, specifically the hierarchical agglomerative clustering of NLP model in real-time settings.

5.3 Analysing Efficiency Gains with AI-integrated Digital Banking

Primarily, it is required to give utmost importance for top management with the integration of AI in the Indian banks. However, it is necessary to implement the plan for a bank-wide comprehensive strategic planning that should provide an action plan for each department in the digital banking industry. Moreover, a systematic and organized banking system need to be developed with full awareness and training of employees with appropriate abilities (Kitsios et al., 2021). The continuous training and education should be provided by system administrators regarding the use of AI in banking services. Furthermore, AI assists the banking organizations to engage the customers through personalization of products and services that given deep analysis of client needs and preferences based on high-speed data processing (Noreen et al., 2023). For that, the complex algorithms of NLP, including hierarchical agglomerative clustering is recommended to be implemented in the designing and implementation of digital financial services, such as monitoring of online transaction and customer account information that showing the rapidity and efficiency compared to the traditional banking techniques. Therefore, the integration of AI techniques would assist the digital banks in preventing the fraud risks, showing direct effect on the financial operations, increasing the accuracy and reliability, acceleration of automated services, improved risk management and asset management, and enhanced customer services.

This study revealed that AI-enabled customer experience (customer available balance and transaction amount using hierarchical agglomerative clustering of NLP classifier with increased Silhouette index of 0.4194) has been affected the customer satisfaction and trust. These findings are aligned with the study of Srinadi et al., (2023), which disclosed that the digital facilities would be relied by the AI-based financial services in banks and the customer impressions with AI-enabled banking services. Therefore, our study given that the integration of AI would cause a shift in the customer experiences regarding the financial services that would build the customer trust. With the integrated customer perspectives that implementing the innovative strategies and technologies, AI-enabled customer experience is build that generated the customer centric views and experiences of customers based on AI capabilities. Thus, the service quality standards of financial products and services would be improved for customers that may also generate the permanent growth in the client demands based on the implementation of AI technologies.

Chapter 6: Conclusion

The impact of AI-enabled customer experience on customer satisfaction and trust through personalization services has been analysed in the digital banking environment. Accordingly, different clustering algorithms of Natural Language Processing (NLP) model were used, in particular, k-Means, DBSCAN, and hierarchical clustering. Out of these three, hierarchical agglomerative clustering outperformed in terms of minimized noise points and increased Silhouette index than the k-Means and DBSCAN methods. In this perspective, hierarchical cluster analysis method may be able to provide great insights to the digital banking industry. This algorithm utilized in this study is effective enough in investigating the customer needs or preferences to achieve the customer trust and satisfaction. Accordingly, the digital banks can make efficient decisions regarding the provision of financial products and services while determining the traits of customers data by detecting the patterns and trends. The results of these data findings can assist the banks in assessing the customer needs and perceptions to gain efficiency of customer satisfaction and trust. This study showed the crucial role of AI in the designing of financial products and services by considering the customer data about online transactions and account balance as fundamental inputs.

6.1 Implications of the Study

The possible implications are highlighted in the study relevant to the implementation of AI technologies in banking sector. However, the automated systems will generate unemployment and make the jobs obsolete. Thus, it is important to adapt the training and education programs for requirements of new digital skills. AI technology has been showed the implications on cybersecurity, in which defensive cyber measures play a crucial role in the applications. The major concern would be data privacy and protection since AI-integrated methods dealing with big data. Therefore, the AI-enabled services in digital banks should ensure data privacy, integrity, and confidentiality. Moreover, the decision-making processes and judgments involved in the AI systems that could necessary to include ethical training programme for AI practitioners in alignment with the existing laws and social norms. In conclusion, AI regulatory approaches should have to be considered for detection of principles to develop the AI and foster the customer experiences.

6.2 Limitations of the Study

The study findings limited to the assessment of AI-enabled customer experience for the Indian digital banking industry while focusing on the impact of AI on the digital financial services. Moreover, other financial products and services also involved with the AI technologies. However, this study was only demonstrated the data findings of customer experience relevant to transaction and account balance in AI-enabled digital services. Future research should recommend to perform the longitudinal analysis based on quantitative data to determine the impact of AI on the financial performance of digital banks through the customer experience and trust.

According to the customer online transactions and account balance, the banking officers can classify the customers data into clusters based on hierarchical clustering methodology. This data can be used to provide informed notifications about their transaction history which will increase customer retention and customer trust eventually. To enhance the customer satisfaction and ensure the trust, the patterns and trends of customer data in each cluster can be considered based on clustering analysis. The data findings of this study can be used to improve the customer experiences by addressing the needs and interests. The efficacy of AI-integrated methods will be evaluated in digital banks and make data-driven decisions for improvement in the patterns of clustering over time. The digital banks can improve financial operations, increase market competitiveness, and improve business value.

References

Agarwal, A., Singhal, C., & Thomas, R. (2021). AI-powered decision making for the bank of the future. *McKinsey & Company*.

Achar, S. (2018). Security of Accounting Data in Cloud Computing: A Conceptual Review. *Asian Accounting and Auditing Advancement*, *9*(1), 60-72.

Akter, S., Michael, K., Uddin, M. R., McCarthy, G., & Rahman, M. (2022). Transforming business using digital innovations: The application of AI, blockchain, cloud and data analytics. *Annals of Operations Research*, 1-33.

Al-Surmi, A., Bashiri, M., & Koliousis, I. (2022). AI based decision making: combining strategies to improve operational performance. *International Journal of Production Research*, *60*(14), 4464-4486.

Alsajjan, B., & Dennis, C. (2010). Internet banking acceptance model: Cross-market examination. *Journal of business research*, *63*(9-10), 957-963.

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in human behavior*, *114*, 106548.

Amin, M. (2016). Internet banking service quality and its implication on e-customer satisfaction and e-customer loyalty. *International journal of bank marketing*, *34*(3), 280-306.

Amrulloh, K., Pudjiantoro, T., Sabrina, P., & Hadiana, A. (2022, May). Comparison Between Davies-Bouldin Index and Silhouette Coefficient Evaluation Methods in Retail Store Sales Transaction Data Clusterization Using K-Medoids Algorithm. In *3rd South American International Conference on Industrial Engineering and Operations Management*.

Ashari, I. F., Banjarnahor, R., Farida, D. R., Aisyah, S. P., Dewi, A. P., & Humaya, N. (2022). Application of data mining with the K-means clustering method and Davies Bouldin index for grouping IMDB movies. *Journal of Applied Informatics and Computing*, *6*(1), 07-15.

Ashta, A., & Herrmann, H. (2021). Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance. *Strategic Change*, *30*(3), 211-222.

Badea, L., Moraru, A. D., Ilie, C., Duhnea, C., & Panait, I. (2021). CUSTOMER SATISFACTION WITH BANKING SERVICES. SIMULATING THE INFLUENCE OF CUSTOMER SATISFACTION DETERMINANTS USING ARTIFICIAL NEURAL NETWORK ALGORITHMS. *Economic Computation & Economic Cybernetics Studies & Research*, *55*(4).

Bag, S., Srivastava, G., Bashir, M. M. A., Kumari, S., Giannakis, M., & Chowdhury, A. H. (2022). Journey of customers in this digital era: Understanding the role of artificial intelligence technologies in user engagement and conversion. *Benchmarking: An International Journal*, *29*(7), 2074-2098.

Berry, L. L., Carbone, L. P., & Haeckel, S. H. (2002). Managing the total customer experience. *MIT Sloan management review*.

Bhatt, V. (2021). An empirical study to evaluate factors affecting customer satisfaction on the adoption of Mobile Banking Track: Financial Management. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(10), 5354-5373.

Buallay, A. (2020). Sustainability reporting and firm's performance: Comparative study between manufacturing and banking sectors. *International Journal of Productivity and Performance Management*, *69*(3), 431-445.

Bushra, A. A., & Yi, G. (2021). Comparative analysis review of pioneering DBSCAN and successive density-based clustering algorithms. *IEEE Access*, *9*, 87918-87935.

Cahapin, E. L., Malabag, B. A., Santiago Jr, C. S., Reyes, J. L., Legaspi, G. S., & Adrales, K. L. (2023). Clustering of students admission data using k-means, hierarchical, and DBSCAN algorithms. *Bulletin of Electrical Engineering and Informatics*, *12*(6), 3647-3656.

Chaitanya, K., Saha, G. C., Saha, H., Acharya, S., & Singla, M. (2023). The Impact of Artificial Intelligence and Machine Learning in Digital Marketing Strategies. *European Economic Letters (EEL)*, *13*(3), 982-992.

Chakrabarti, R., & Sanyal, K. (2020). Towards a 'Responsible AI': can India take the lead?. *South Asia Economic Journal*, *21*(1), 158-177.

Chakraborti, T., Isahagian, V., Khalaf, R., Khazaeni, Y., Muthusamy, V., Rizk, Y., & Unuvar, M. (2020). From Robotic Process Automation to Intelligent Process Automation: –Emerging Trends–. In *Business Process Management: Blockchain and Robotic Process Automation*

Forum: BPM 2020 Blockchain and RPA Forum, Seville, Spain, September 13–18, 2020, Proceedings 18 (pp. 215-228). Springer International Publishing.

Chen, Z., Li, Y., Wu, Y., & Luo, J. (2017). The transition from traditional banking to mobile internet finance: an organizational innovation perspective-a comparative study of Citibank and ICBC. *Financial Innovation*, *3*(1), 12.

Cherinet, E. M. (2022). *8 Factors That Drive Digital Transformation in Banking Industry* [Online]. Available at: https://www.linkedin.com/pulse/8-factors-drive-digital-transformation-banking-mesfin-cherinet/ (Accessed: 11 April 2024).

Chugunova, M., & Sele, D. (2020). We and it: An interdisciplinary review of the experimental evidence on human-machine interaction. *Center for law & economics working paper series*, *12*.

Cortiñas, M., Chocarro, R., & Villanueva, M. L. (2010). Understanding multi-channel banking customers. *Journal of Business Research*, *63*(11), 1215-1221.

Curran, J. M., & Meuter, M. L. (2005). Self- service technology adoption: comparing three technologies. *Journal of services marketing*, *19*(2), 103-113.

Daqar, M. A. A., & Smoudy, A. K. (2019). The role of artificial intelligence on enhancing customer experience. *International Review of Management and Marketing*, *9*(4), 22.

de Marcellis-Warin, N., Marty, F., Thelisson, E., & Warin, T. (2022). Artificial intelligence and consumer manipulations: from consumer's counter algorithms to firm's self-regulation tools. *AI and Ethics*, *2*(2), 259-268.

Demirel, D. (2022). The effect of service quality on customer satisfaction in digital age: customer satisfaction based examination of digital CRM. *Journal of Business Economics and Management*, *23*(3), 507-531.

Desaulniers, S. (2016). Chatbots rise, and the future may be ‘re-written’. *CNBC. com, April, 10*.

Dootson, P., Beatson, A., & Drennan, J. (2016). Financial institutions using social media–do consumers perceive value?. *International Journal of Bank Marketing*, *34*(1), 9-36.

Dreyer, T. (2016). Survey finds half of consumers would prefer to conduct all customer service via messaging.

Duarte, P., e Silva, S. C., & Ferreira, M. B. (2018). How convenient is it? Delivering online shopping convenience to enhance customer satisfaction and encourage e-WOM. *Journal of Retailing and Consumer Services*, *44*, 161-169.

Fatmawati, I., & Fauzan, N. (2021). Building customer trust through corporate social responsibility: The Effects of corporate reputation and word of mouth. *The Journal of Asian Finance, Economics and Business*, *8*(3), 793-805.

French, S., Leyshon, A., & Meek, S. (2013). The changing geography of British bank and building society branch networks, 2003-2012.

George, A. S., & George, A. H. (2023). A review of ChatGPT AI's impact on several business sectors. *Partners Universal International Innovation Journal*, *1*(1), 9-23.

Gorla, N., Somers, T. M., & Wong, B. (2010). Organizational impact of system quality, information quality, and service quality. *The Journal of Strategic Information Systems*, *19*(3), 207-228.

Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, *3*, 119-132.

Hanafizadeh, P., Behboudi, M., Koshksaray, A. A., & Tabar, M. J. S. (2014). Mobile-banking adoption by Iranian bank clients. *Telematics and informatics, 31*(1), 62-78.

Hassan, I. H., Abdullahi, M., & Ali, Y. S. (2021). Analysis of Techniques for Selecting Appropriate Number of Clusters in K-means Clustering Algorithm. *no. November*.

Hoehle, H., Scornavacca, E., & Huff, S. (2012). Three decades of research on consumer adoption and utilization of electronic banking channels: A literature analysis. *Decision Support Systems, 54*(1), 122-132.

Hussain, M. M., Amin, Z., & Rasool, N. (2023). Roshan Digital Account: A Digital Innovation in Pakistan and its Impact on Customers' Satisfaction. *Journal of Development and Social Sciences*, *4*(1), 36-52.

Indriasari, E., Gaol, F. L., & Matsuo, T. (2019). Digital banking transformation: Application of artificial intelligence and big data analytics for leveraging customer experience in the Indonesia banking sector. In *2019 8th International Congress on Advanced Applied Informatics (IIAI-AAI)* (pp. 863-868). IEEE.

Jia, W., Sun, M., Lian, J., & Hou, S. (2022). Feature dimensionality reduction: a review. *Complex & Intelligent Systems, 8*(3), 2663-2693.

Jun, M., & Palacios, S. (2016). Examining the key dimensions of mobile banking service quality: an exploratory study. *International Journal of Bank Marketing*, *34*(3), 307-326.

Karahanli, N. G., & Touma, J. (2021). Digitalization of the customer experience in banking Use of AI and SSTs in complex/sensitive tasks: pre-collection.

Kaur, N., & Kiran, R. (2015). E-banking service quality and customer loyalty: Changing dynamics of public, private and foreign bank consumers in India. *Global Business and Management Research*, *7*(1), 74.

Kaur, S. J., Ali, L., Hassan, M. K., & Al-Emran, M. (2021). Adoption of digital banking channels in an emerging economy: exploring the role of in-branch efforts. *Journal of Financial Services Marketing*, *26*, 107-121.

Kaura, V., Durga Prasad, C. S., & Sharma, S. (2015). Service quality, service convenience, price and fairness, customer loyalty, and the mediating role of customer satisfaction. *International journal of bank marketing*, *33*(4), 404-422.

Kazmi, S. H. A., Ahmed, R. R., Soomro, K. A., Hashem E, A. R., Akhtar, H., & Parmar, V. (2021). Role of augmented reality in changing consumer behavior and decision making: Case of Pakistan. *Sustainability*, *13*(24), 14064.

Keiningham, T., Aksoy, L., Bruce, H. L., Cadet, F., Clennell, N., Hodgkinson, I. R., & Kearney, T. (2020). Customer experience driven business model innovation. *Journal of Business Research*, *116*, 431-440.

Keisidou, E., Sarigiannidis, L., Maditinos, D. I., & Thalassinos, E. I. (2013). Customer satisfaction, loyalty and financial performance: A holistic approach of the Greek banking sector. *International Journal of Bank Marketing*, *31*(4), 259-288.

Khalid, S., Khalil, T., & Nasreen, S. (2014, August). A survey of feature selection and feature extraction techniques in machine learning. In *2014 science and information conference* (pp. 372-378). IEEE.

Khan, S. K., ul Hassan, N., & Anjum, M. N. (2022). FACTORS INFLUENCING CUSTOMER SATISFACTION IN E-BANKING SERVICES IN PAKISTAN: EVIDENCE BASED ON RELIABILITY, PRIVACY & CONVENIENCE. *Journal of Social Research Development*, *3*(2), 286-296.

Kietzmann, J., Paschen, J., & Treen, E. (2018). Artificial intelligence in advertising: How marketers can leverage artificial intelligence along the consumer journey. *Journal of Advertising Research*, *58*(3), 263-267.

Kim, E. Y., & Yang, K. (2018). Self-service technologies (SSTs) streamlining consumer experience in the fashion retail stores: The role of perceived interactivity. *Journal of Global Fashion Marketing*, *9*(4), 287-304.

Kitsios, F., Giatsidis, I., & Kamariotou, M. (2021). Digital transformation and strategy in the banking sector: Evaluating the acceptance rate of e-services. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(3), 204.

Klaus, P. P., & Maklan, S. (2013). Towards a better measure of customer experience. *International journal of market research*, *55*(2), 227-246.

Kübler, R. V., Colicev, A., & Pauwels, K. H. (2020). Social media's impact on the consumer mindset: When to use which sentiment extraction tool?. *Journal of Interactive Marketing*, *50*(1), 136-155.

Lai- Ming Tam, J. (2012). The moderating role of perceived risk in loyalty intentions: an investigation in a service context. *Marketing Intelligence & Planning*, *30*(1), 33-52.

Li, F., Lu, H., Hou, M., Cui, K., & Darbandi, M. (2021a). Customer satisfaction with bank services: The role of cloud services, security, e-learning and service quality. *Technology in Society*, *64*, 101487.

Li, T., Kou, G., Peng, Y., & Philip, S. Y. (2021b). An integrated cluster detection, optimization, and interpretation approach for financial data. *IEEE transactions on cybernetics*, *52*(12), 13848-13861.

Lin, H. F. (2011). An empirical investigation of mobile banking adoption: The effect of innovation attributes and knowledge-based trust. *International journal of information management*, *31*(3), 252-260.

Lusardi, A. (2019). Financial well-being of the Millennial generation: An in-depth analysis of its drivers and implications. *Global Financial Literacy Excellence Center*, 1-7.

Machlev, R., Tolkachov, D., Levron, Y., & Beck, Y. (2020). Dimension reduction for NILM classification based on principle component analysis. *Electric Power Systems Research*, *187*, 106459.

Madavan, K., & Vethirajan, C. (2020). Customer satisfaction on E-banking services of public and private sector banks in puducherry region-an empirical analysis. *International Journal of Management (IJM)*, *11*(6), 649-664.

Manser Payne, E., Peltier, J. W., & Barger, V. A. (2017). Omni-channel marketing, integrated marketing communications and consumer engagement: A research agenda. *Journal of Research in Interactive Marketing*, *11*(2), 185-197.

Manser Payne, E. H., Peltier, J., & Barger, V. A. (2021). Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms. *Journal of Research in Interactive Marketing*, *15*(1), 68-85.

Manser Payne, E. H., Dahl, A. J., & Peltier, J. (2021). Digital servitization value co-creation framework for AI services: a research agenda for digital transformation in financial service ecosystems. *Journal of Research in Interactive Marketing*, *15*(2), 200-222.

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International journal of information management*, *34*(1), 1-13.

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM computing surveys (CSUR)*, *54*(6), 1-35.

Meuter, M. L., Ostrom, A. L., Roundtree, R. I., & Bitner, M. J. (2000). Self-service technologies: understanding customer satisfaction with technology-based service encounters. *Journal of marketing*, *64*(3), 50-64.

Mogaji, E., Adeola, O., Hinson, R. E., Nguyen, N. P., Nwoba, A. C., & Soetan, T. O. (2021). Marketing bank services to financially vulnerable customers: evidence from an emerging economy. *International Journal of Bank Marketing*, *39*(3), 402-428.

Mols, N. P. (2001). Organizing for the effective introduction of new distribution channels in retail banking. *European Journal of Marketing*, *35*(5/6), 661-686.

Monferrer-Tirado, D., Estrada-Guillén, M., Fandos-Roig, J. C., Moliner-Tena, M. Á., & Sanchez Garcia, J. (2016). Service quality in bank during an economic crisis. *International Journal of Bank Marketing*, *34*(2), 235-259.

Mousavi, S. H. A. H. L. A., Boroujeni, F. Z., & Aryanmehr, S. A. E. E. D. (2020). Improving customer clustering by optimal selection of cluster centroids in K-means and K-medoids algorithms. *Journal of Theoretical and Applied Information Technology*, *98*(18), 3807-3814.

Munappy, A., Bosch, J., Olsson, H. H., Arpteg, A., & Brinne, B. (2019, August). Data management challenges for deep learning. In *2019 45th Euromicro Conference on Software Engineering and Advanced Applications (SEAA)* (pp. 140-147). IEEE.

Murugesan, N., Cho, I., & Tortora, C. (2021). Benchmarking in cluster analysis: a study on spectral clustering, DBSCAN, and K-Means. In *Data Analysis and Rationality in a Complex World 16* (pp. 175-185). Springer International Publishing.

Nguyen, H. B., Xue, B., Liu, I., & Zhang, M. (2014, July). Filter based backward elimination in wrapper based PSO for feature selection in classification. In *2014 IEEE congress on evolutionary computation (CEC)* (pp. 3111-3118). IEEE.

Noreen, U., Shafique, A., Ahmed, Z., & Ashfaq, M. (2023). Banking 4.0: Artificial intelligence (AI) in banking industry & consumer's perspective. *Sustainability*, *15*(4), 3682.

Oliveira, P., & von Hippel, E. (2011). Users as service innovators: The case of banking services. *Research policy*, *40*(6), 806-818.

Osei, L. K., Cherkasova, Y., & Oware, K. M. (2023). Unlocking the full potential of digital transformation in banking: a bibliometric review and emerging trend. *Future Business Journal*, *9*(1), 30.

Pakurar, M., Haddad, H., Nagy, J., Popp, J., & Oláh, J. (2019). The service quality dimensions that affect customer satisfaction in the Jordanian banking sector. *Sustainability*, *11*(4), 1113.

Pazarbasioglu, C., Mora, A. G., Uttamchandani, M., Natarajan, H., Feyen, E., & Saal, M. (2020). Digital financial services. *World Bank*, *54*.

Punhani, A., Faujdar, N., Mishra, K. K., & Subramanian, M. (2022). Binning-based silhouette approach to find the optimal cluster using K-means. *IEEE Access*, *10*, 115025-115032.

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing*, *85*(1), 131-151.

Riyadi, S. (2021). The effects of image, brand and quality on customer loyalty of sharia banking. *The Journal of Asian Finance, Economics and Business*, *8*(3), 1315-1325.

Sagala, N. T., & Gunawan, A. A. S. (2022). Discovering the optimal number of crime cluster using elbow, silhouette, gap statistics, and nbclust methods. *ComTech: Computer, Mathematics and Engineering Applications*, *13*(1), 1-10.

Sarker, I. H. (2022). AI-based modeling: techniques, applications and research issues towards automation, intelligent and smart systems. *SN Computer Science*, *3*(2), 158.

Sarokolaei, M. A., Rahimipoor, A., Nadimi, S., & Taheri, M. (2012). The investigating of barriers of development of e-banking in Iran. *Procedia-Social and Behavioral Sciences*, *62*, 1100-1106.

Schlicht, M. (2016). The complete beginner's guide to chatbots. *Chatbots magazine*, *20*.

Sundarraj, R. P., & Wu, J. (2005). Using information-systems constructs to study online-and telephone-banking technologies. *Electronic Commerce Research and Applications*, *4*(4), 427-443.

Schwartz, R., Schwartz, R., Vassilev, A., Greene, K., Perine, L., Burt, A., & Hall, P. (2022). *Towards a standard for identifying and managing bias in artificial intelligence* (Vol. 3, p. 00). US Department of Commerce, National Institute of Standards and Technology.

Setiono, B. A., & Hidayat, S. (2022). Influence of Service Quality with the Dimensions of Reliability, Responsiveness, Assurance, Empathy and Tangibles on Customer Satisfaction. *International Journal of Economics, Business and Management Research*, *6*(09), 330-341.

Shareef, M. A., Baabdullah, A., Dutta, S., Kumar, V., & Dwivedi, Y. K. (2018). Consumer adoption of mobile banking services: An empirical examination of factors according to adoption stages. *Journal of Retailing and Consumer Services*, *43*, 54-67.

Shen, C., & Zhang, K. (2022). Two-stage improved Grey Wolf optimization algorithm for feature selection on high-dimensional classification. *Complex & Intelligent Systems*, *8*(4), 2769-2789.

Sheth, J. N., Jain, V., Roy, G., & Chakraborty, A. (2022). AI-driven banking services: the next frontier for a personalised experience in the emerging market. *International Journal of Bank Marketing*, *40*(6), 1248-1271.

Singh, S. (2024). *Digital Transformation in Banking: What it means for businesses* [Online]. Available at: https://appinventiv.com/blog/digital-transformation-in-banking/ (Accessed: 04 April 2024).

Srinadi, N. L. P., Hermawan, D., & Jaya, A. A. N. A. (2023). Advancement of banking and financial services employing artificial intelligence and the internet of things. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, *14*(1), 106-117.

Taleghani, M., Gilaninia, S., & Mousavian, S. J. (2011). The role of relationship marketing in customer orientation process in the banking industry with focus on loyalty (Case study: Banking industry of Iran). *International journal of business and social science*, *2*(19).

Tam, C., & Oliveira, T. (2017). Literature review of mobile banking and individual performance. *International Journal of Bank Marketing*, *35*(7), 1044-1067.

Tham, J., Ab Yazid, M. S., Khatibi, A. A., & Azam, S. F. (2017). Internet and data security–understanding customer perception on trusting virtual banking security in Malaysia. *European Journal of Social Sciences Studies*.

Theuri, J., & Olukuru, J. (2022). *The impact of Artficial Intelligence and how it is shaping banking* (No. 61). KBA Centre for Research on Financial Markets and Policy Working Paper Series.

Teo, C., Anderson, D., Fenwick, N., & Ying, Z. N. (2014). The State Of Digital Business in Asia Pacific in 2019.

Trivedi, J. (2019). Examining the customer experience of using banking chatbots and its impact on brand love: The moderating role of perceived risk. *Journal of internet Commerce*, *18*(1), 91-111.

Tulcanaza-Prieto, A. B., Cortez-Ordoñez, A., & Lee, C. W. (2023). Influence of Customer Perception Factors on AI-Enabled Customer Experience in the Ecuadorian Banking Environment. *Sustainability*, *15*(16), 12441.

Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal*, *26*(7), 1893-1924.

Wilbert, H. J., Hoppe, A. F., Sartori, A., Stefenon, S. F., Silva, L. A., & Leithardt, V. R. Q. (2023). Using Clustering for Customer Segmentation from Retail Data.

Xue, M., Hitt, L. M., & Chen, P. Y. (2011). Determinants and outcomes of internet banking adoption. *Management science*, *57*(2), 291-307.

Yee, R. W., Yeung, A. C., & Cheng, T. E. (2010). An empirical study of employee loyalty, service quality and firm performance in the service industry. *International Journal of Production Economics*, *124*(1), 109-120.

Yiu, C. S., Grant, K., & Edgar, D. (2007). Factors affecting the adoption of Internet Banking in Hong Kong—implications for the banking sector. *International journal of information management*, *27*(5), 336-351.

Yoon, C. (2010). Antecedents of customer satisfaction with online banking in China: The effects of experience. *Computers in Human Behavior*, *26*(6), 1296-1304.

Zebari, R., Abdulazeez, A., Zeebaree, D., Zebari, D., & Saeed, J. (2020). A comprehensive review of dimensionality reduction techniques for feature selection and feature extraction. *Journal of Applied Science and Technology Trends, 1*(1), 56-70.

Zhou, S., Xu, Z., & Liu, F. (2016). Method for determining the optimal number of clusters based on agglomerative hierarchical clustering. *IEEE transactions on neural networks and learning systems*, *28*(12), 3007-3017.