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KEY DRIVERS AND MACHINE LEARNING IN PERSONALIZED MOBILE BANKING

Opportunities and challenges for retail banks

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Abstract

This thesis explores the integration of AI-driven personalization into retail banks' mobile banking services. It investigates the opportunities and challenges arising from this convergence as retail banks seek to fulfil customer expectations for convenience and engagement in the retail financial sector. Consumer expectations for personalized services are on the rise, creating a dynamic where companies must navigate the balance between personalization and cost-effectiveness in the development of mobile banking. To comprehensively analyse this, a broad literature review is chosen as the research method.

The findings reveal that AI-powered personalization holds promise in enhancing user engagement but poses challenges related to scalability. Tailoring strategies to the unique needs and preferences of each customer segment is crucial. Transparency, user control and user empowerment are key factors in building trust in AI-driven financial services. In summary, this thesis offers insights into the potential of applying machine learning algorithms to enrich and personalize the mobile banking experience for retail banks, giving insights to retail banks, and researchers alike.

Keywords mobile banking development, AI-driven personalization, banking, machine learning, customer clustering, recommendation systems

Table of Contents

List of Figures

1 Introduction

1.1 Background and Overview

In the past, bank managers would personally know their local customers, understanding their financial situation, preferences, and history. This allowed banks to provide personalized financial services through face-to-face delivery and match the right services to the right customers. However, with the rise of online banking and increasing competition, banks have shifted to delivering services digitally and through automation with minimal human interaction to remain competitive.

The traditional personalized service model has mainly survived only in commercial banking and private banking. Personalized interactions in banking have therefore diminished and banks are looking again to personalize their services and user experience to differentiate themselves but with the utilization of technology. Banks are now aiming to improve the personalization of their services while still maintaining cost-efficiency (Wells et al., 2000).

Artificial intelligence (AI) and machine learning (ML) are two rapidly developing technologies with the potential to revolutionize many industries, including (personalized) mobile banking. As defined by Russell and Norvig (2009), AI is the study of "intelligent agents": systems that can reason, learn, and act autonomously. ML is on the other hand a subset of AI that focuses on developing algorithms that can learn from data and improve their performance over time.

According to Srinivas and Wadhwani (2018), mobile banking is a rapidly growing industry as many banks are prioritizing mobile banking, launching mobile-only brands, or adding new features to their apps. Online banking, of which mobile banking is a sub-category, remains relevant, with 73% of respondents in a Deloitte survey using it at least once a month, compared to 59% for mobile banking apps which is still quite significant.

For the banking industry, artificial intelligence (AI) can come into play as AI can significantly increase bank profitability by reducing costs and in-creasing productivity. Rapid adoption of AI is essential for banks to remain competitive, especially in the rapidly growing online and mobile banking sector (Kaya et al., 2019). Additionally, the exponential growth of data in the digital banking landscape has led to the emergence of big data, which has been a driving factor in the implementation of AI algorithms. (Kaya et al., 2019). Big data is essential for AI- and machine learning (ML)-driven decision-making, as it empowers ML algorithms to uncover more specific patterns and make more prompt and precise predictions (Zhou et al., 2017).

As a result of technological advancements, online banking presents a transformative opportunity, particularly within the banking sector that has traditionally relied on physical branches for customer service provision (Bradley & Stewart, 2003). In addition to cost reductions, (Kaya et al., 2019) argues that the implementation of AI and machine learning in banking has also significant potential for gains in revenue. Shahid et al. (2022) describes mobile banking as a "win-win cost-effective strategy for both account holders and banks," noting that it saves users time and money and helps banks save on costs associated with maintaining physical branches. Additionally, it is intriguing and highly relevant to note that the personalization of mobile banking is closely intertwined with machine learning which presents banks the potential to deepen the understanding of their customers better and craft more precise marketing campaigns (Dawood et al., 2019; Carbo-Valverde et al., 2020;).

1.2 Research objectives and research questions

This thesis delves into the key drivers and potential integration of AI-driven personalization into the mobile banking services of retail banks. It explores the potential and challenges associated with this convergence, as retail banks strive to develop new solutions with the focus on meeting the needs of their customers in the financial sector (Alt, Beck, & Smits, 2017).

The approach of the study is to do and provide a comprehensive literature review within this diverse topic, integrating insights from finance, marketing, and technology. This approach provides a comprehensive understanding of the current landscape and the untapped potential of AI-powered personalization in banking. This research also aims to address and assess challenges involved in personalization efforts such as the paradox between personalization and data privacy as such challenges need to be addressed for successful implementation and mature usage (Albashrawi, M., & Motiwalla, L. 2019).

Therefore, the overarching goal of this research is to analyse key drivers behind personalization, investigate the integration of AI-driven personalization on mobile banking and explore benefits both for customers and banks. The specific research questions that guide this investigation are as follows:

- *What are the key aspects of personalized mobile banking, and how do they impact both, customers, and banks?*

- *How do customer demographics, behaviour, and preferences influence the effectiveness of personalization in mobile banking?*

- *How can financial institutions integrate personalization into mobile banking platforms effectively?*

- *What is the impact of machine learning algorithms in mobile banking, especially in customer classification, user interface personalization, and customer segmentation?*

- *What are the challenges in developing and employing complex machine learning models in mobile banking?*

1.3 Methodology

Throughout this research, a wide range of data sources were collected from repositories such as Scopus and Google Scholar. The literature review consisted mainly of scientific articles, and the "filters" used to ensure the quality and relevance of the sources were the impact factor, release year and in a couple cases the number of citations. In addition, other sources were included, such as theoretical books on AI focusing on machine learning, as well as studies and articles from major international consulting firms such as Deloitte, McKinsey, CGI, and others. Given the inherent diversity of the topic, as AI-based personalisation covers many areas of marketing and technology, it must be acknowledged that this wide range of sources may have influenced the findings of the study.

1.4 Structure of the research

This thesis is structured into five main chapters to thoroughly explore the opportunities and challenges of the integration of AI-driven personalization in mobile banking, assess its key drivers and potential implementation of machine learning algorithms to personalize the mobile banking experience. Therefore, the rest of the thesis is structured as follows:

Chapter 1 sets the stage for this thesis by providing a comprehensive introduction and background overview to the personalization of mobile banking using AI and machine learning. This chapter explores the significance of AI-driven personalization in enhancing user engagement, improving financial services, and catering to the distinct requirements of mobile banking customers. It outlines the research questions that guide the investigation, defines the scope of the research, and outlines the methodology used for collecting and analysing data.

Chapter 2 delves into the factors driving the emergence of AI-driven personalization in mobile banking. It examines four key drivers based on the prevalence in literature review: the increased availability of customer data, advancements in AI and ML technologies, the growing recognition of personalization benefits, and the role of customer-centric Big Data analytics. Each driver contributes uniquely to the landscape of AI-driven personalization within mobile banking.

Chapter 3 introduces and then explores some machine learning algorithms to illustrate the aspects of personalization that can be potentially achieved in mobile banking through these advanced algorithms. It delves into three categories: super-vised learning algorithms, unsupervised learning algorithms, and reinforced learning algorithms. Each category is examined in detail, highlighting their potential applications, strengths, and limitations in the context of personalization within mobile banking.

Chapter 4 presents the findings derived from the exploration of AI-driven personalization in mobile banking. This chapter encapsulates the key insights and findings made throughout the research. It analyses the role of key drivers of AI-driven personalization and the implementation of machine learning algorithms in this context. The findings aim provide a comprehensive overview of the landscape of AI-driven personalization within mobile banking.

Chapter 5 discusses the literature review but ties the assessments and analysis back into the research questions. This chapter evaluates the integration of machine learning algorithms for personalized mobile banking. This chapter aligns with existing academic research but also contributes new perspectives with by going over implications, limitations, and suggestions for future research.

2 Key Drivers of AI-driven Personalization in Mobile Banking

The financial services industry is undergoing a transformative shift driven by technological advancements, particularly related to artificial intelligence (AI) and its subset of machine learning (ML) (Turban et al., 2020). These technologies are not only utilized by banks to automate various processes but also revolutionizing their services, providing personalized and innovative financial solutions that were once unimaginable (Vargo et al., 2018; O'Connor, 2019;). Within this dynamic landscape, mobile banking has emerged as a critical channel for customer engagement and financial transactions (Klapper et al., 2016; Chen & Lim, 2019). To meet the rising expectations of consumers seeking seamless and personalized digital experiences (Barnes & Corbitt, 2002; Lemon & Verhoef, 2016), retail banks are implementing AI solutions to enhance their mobile banking platforms (Hsieh et al., 2015; Zhang et al., 2019).

The advancement of AI and ML holds the potential to reshape the landscape of customer experience and services in banking (Kaya et al., 2019; Accenture, 2021). By leveraging AI-powered solutions, banks can significantly increase the volume of interactions and transactions without expanding their workforce, potentially lowering their cost-income ratio be-low 30%. (Accenture, 2021). This integration of AI into banking is a promising avenue for cost reduction, addressing the increasing pressure on banks to optimize their operations and improve financial performance (Wells et al., 2000).

Brun et al. (2014) assert that banks should prioritize and invest in web-based relationship strategies emphasizing a strong focus on customer needs as a critical determinant of success. New marketing practices based on personalization have tackled this role and contribute to this perspective. Examples of this include database marketing, which involves collecting consumer data for behaviour tracking and targeted marketing, and integrated marketing communications, focusing on coordinating various tools and channels for effective customer interaction.

A more recent study by Sheth et al. (2022) also supports this idea of web-based relationship management for banks through the development of personalized banking but with the combination of synergetic human-AI operation. In this study, financial consultants and bank managers from South Asian countries were interviewed about their opinions on personalized banking and the combination of human-AI banking. In addition, in the study they proposed the following framework on human-AI banking services based on their summary of literature. As illustrated in Figure 1 (Sheth et al., 2022), this framework not only encapsulates the idea of human-AI operation in banking but also visually represents different themes that are central to this thesis topic, which is AI-driven personalization of mobile banking.

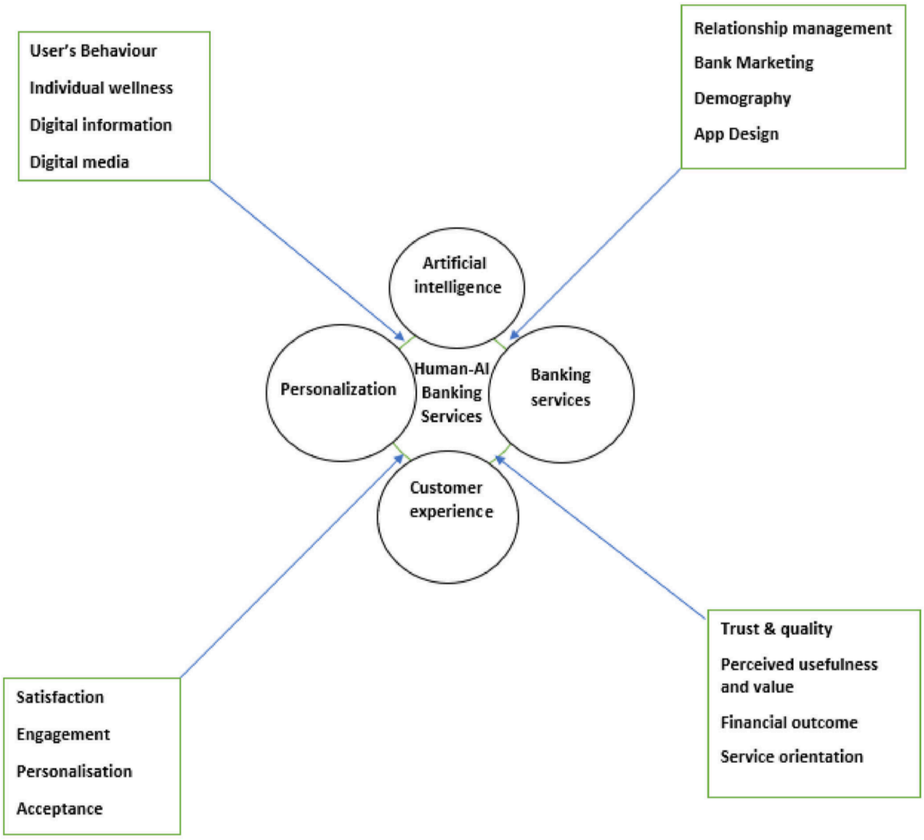

Figure 1. (Sheth et al., 2022)

In the aspect of mobile banking, AI-powered interactions range from low- to high value activities - from basic transactions to advanced financial advice. Banks are increasingly using AI to provide a more personalized and secure banking experience (Manser Payne, Peltier, & Barger, 2021). This shift towards personalized mobile banking experiences is driven by several factors. Based on the literature review, we introduce and discuss the prevalent factors behind this shift towards personalization in the mobile banking environment.

2.1 Increased availability of customer data

The digital age has led to an explosion of structured data generated by mil-lions of IoT devices. Additionally, the growth of data intensifies with the influx of unstructured data from internet users. These users contribute to both structured and unstructured data with web browsing information captured through click sequences, delays, and substantial amounts of un-structured data. Leveraging AI for the analysis of this data can be highly valuable for practicioners in the financial industry. AI-driven analysis can unveil more abstract patterns and insights into app usage and user behaviour (O'Leary, 2013).

Overall, data has become a crucial resource in the financial industry, driving innovation and transforming various financial services. The integration of big data technology into banking services is has led to an abundance of data that can be harnessed for improved decision-making and personalized customer experiences (Hasan, Popp, & Oláh, 2020). However, the mere integration of this technology proves insufficient in the mobile banking (MB) and financial service personalization. According to Albashrawi and Moti-walla's study (2019), there is an imperative for banks to refine their data analytics and collection practices.

The continuous stream of data is crucial for utilizing AI (Accenture, 2021). It provides a basis for AI algorithms to play a crucial role in tasks such as pattern recognition, learning, structured interpretation, and other intricate processes, especially when dealing with extensive and large datasets. Additionally, the integration of parallel processing into ML algorithms is a promising approach to the need for scalable solutions (O'Leary, 2013).

2.2 Advancing AI and ML technologies

The continuous development of AI and ML has led and continues to lead to significant advances and improved capabilities of algorithms, enabling them to handle large datasets, interpret complex patterns and provide predictive insights (Alkurd et al., 2020). According to Kumar et al. (2019), the advancement of AI and deep learning has notably transformed the landscape of personalization across diverse industries.

Prior to the widespread adoption of AI, mass personalization for banks in general was considered economically unfeasible due to the substantial manual effort and data analysis involved. For banks, creating marketing messages and offerings for each local or regional area not only proves to be labour-intensive for banks but also incurs significant costs and inefficiencies, resulting in a substantial portion of the audience being left unserved. Addressing this challenge by expanding personalization beyond regional and local levels to smaller segments or individual customers would introduce an even higher level of complexity and labour requirements without AI-integrated solutions (Kumar et al., 2019).

Therefore, the advent of AI technologies has revolutionised mobile banking personalisation, removing the limitations of traditional approaches and enabling banks to provide seamless, intuitive and cost-effective experiences for their customers (Chung et al., 2020). This type of mass personalisation and customisation is now affordable and possible thanks to new technological advancements (Wind, 2001). Thus, the integration of AI and ML technologies stands out as a key driver for better feasibility and efficiency of personalized experiences in mobile banking.

Additionally, technological advancements and their integration are already evident in real-world applications in terms of personalization. Villar and Khan (2021) in their case study on robotic process automation (RPA) in Deutsche Bank highlight that technological advancements overall are driving banks to enhance service quality while simultaneously having to optimize their operations and lower expenses. This study shows that banks are improving service quality and customer experience not only through process automation, but also by combining cognitive technologies such as machine learning with automation to provide more targeted and personalised services.

In the aspect of mobile banking, AI therefore acts is a key enabler for the high degree of personalization in the user experience (Manser Payne et al., 2021) whereas machine learning algorithms enable AI systems to learn from data and improve their performance over time (Vrontis et al., 2022; Soori et al., 2023). This symbiotic relationship between AI and ML has driven the evolution of personalized digital marketing (Kumar et al., 2019).

2.3 Growing recognition of personalization benefits

Banks are increasingly recognising the benefits of personalization, as customers are expecting more from companies they interact with in terms of understanding their true needs, wants and desires (Deloitte, 2022). The convenience and relevance of personalized experiences are highly valued by customers, as demonstrated by Huang and Lin's (2005) research on customer-oriented financial service personalization.

Banks acknowledge the potential of personalization which fuels the implementation, including customized products and user interfaces, to enhance customer engagement, satisfaction, and loyalty (Huang & Lin, 2005; Noreen et al., 2023). The development of highly customized products is less costly for digital products such as financial services. This is both promising for customers and banks as customers are starting to have better access to more personalized and tailored financial services which banks can now provide with reasonable costs and speed in terms of product and service delivery (Wind, 2001). These points align with McKinsey & Company's 2020 research which also suggests that the banks of the future should acknowledge these benefits, positioning AI-driven personalization as the foundational layer for cultivating customer engagement.

A study by Ball et al. (2006) proposes that personalization positively impacts customer satisfaction and trust, which in turn leads to increased loyalty. Huang and Lin's 2005 research indicates that co-value personalization is achievable when users can customize their experiences and retain control over both privacy and the information they receive. When users feel that their financial institution understands and caters to their needs, they are more likely to also remain customers over the long term.

Banks understand these benefits of developing highly personalized and customized products, services, and user experiences, that reflect the traditional model of personalized banking (Wells et al., 2000). However, they should not overly focus on the potential benefits and opportunities associated with creating personalized and customized service as excessive personalization can inadvertently lead to overwhelming customers and overcomplicating service delivery. Additionally, customer privacy concerns can limit personalization efforts and diminish their effectiveness (Wind, 2001). Despite the concerns over data privacy, Wells et al. (2000) argue that banks can still effectively collect and use customer data for personalization purposes without compromising the privacy of customers.

2.4 Customer-centric Big Data Analytics

Deloitte's research in 2011 underlines the role of customer analytics in modern banking, where customer preferences and behaviours are constantly reshaped by technological advancements. Such advancements in AI, ML, data availability, and analytics have created new opportunities for analytics in the banking sector (McKinsey, 2017). The same study by Deloitte (2011) however, strongly emphasizes on the need for banks to enhance their customer-centric analytics across four critical domains: 1) Customer acquisition, 2) Service optimization, 3) Relationship development, and 4) Customer retention. In the context of personalization, these aspects hold relevance, as this study also argued that customers are more likely to exhibit loyalty based on factors beyond mere price when they perceive attention on a personalized level.

However, delivering highly personalized financial services requires deep and diverse understanding and analysis of customers and their behaviour and preferences. These are necessary for improving customer loyalty (Wells et al., 2000) and represents the most common approach to personalize customer experiences (Schiaffino, S., & Amandi, A., 2004). This is where high volumes of data come into play. As data volumes rise, the depth of this data analysis becomes even more essential and serves as a key for technological progress (Osisanwo et al., 2017).

In Kamel's (2023) study, a key emphasis is placed on the pivotal role played by Big Data Analytics (BDA) and data-driven Customer Relationship Management (CRM) strategies in empowering businesses to enhance both their performance and competitive edge. By harnessing BDA for deep customer insights, companies can tailor offerings and marketing even to individual preferences, boosting customer engagement and loyalty. (Noreen et al., 2023) Such deep and comprehensive customer insights are essential because banks must gain a deeper understanding of their customers to remain competitive (Chaban, M., 2021).

According to the Deutsche Bank case study by Villar and Khan (2021) also demonstrates that combining BDA with AI-driven automation can be valuable for personalization efforts in banking. This case study showcases the advantages of integrating BDA with cognitive robotic process automation (CRPA) de-fined as the use of software to automate various tasks and processes based on configuration and rules but also incorporates machine learning. This combination offers insights for banks in terms of improving customer experiences, identifying business patterns, and optimizing internal operations – all components for personalization strategies.

According to McKinsey (2017), analytics can bring significant value to banks by improving customer retention, revenue generation, and risk management. Nevertheless, it is important to note that this study highlights that the potential is constrained by the challenges banks face in scaling up their analytics initiatives. One promising avenue to address this challenge in scalability for is through the integration of AI-driven analytics. AI-powered analytics have the capability to leverage customer data and behaviour patterns also in real time, holding the potential for cost-effective personalization of mobile banking which aligns with individual preferences and needs (Chung et al., 2020).

Additionally, the high volume and complexity of big data pose challenges for implementing personalized recommendation systems on a large scale. Current algorithms struggle to keep recommendations accurate and reliable as they continuously handle streams of complex and detailed user data, further complicated by dynamic user behaviour (Xiao et al., 2020). For personalized mobile banking, this means it is not effortless to process and analyse large this type of user data to generate personalized and accurate recommendations. This challenge is heightened when considering the diverse range of data types that need to be analysed, such as personal information, financial behaviour, device information and location data.

Presented in Figure 2, this theoretical framework concludes the literature review by encapsulating the key drivers of personalization in mobile banking, grounded in the reviewed research. It identifies these discussed factors, which are widely considered in research to be key drivers of AI-driven personalization in mobile banking.

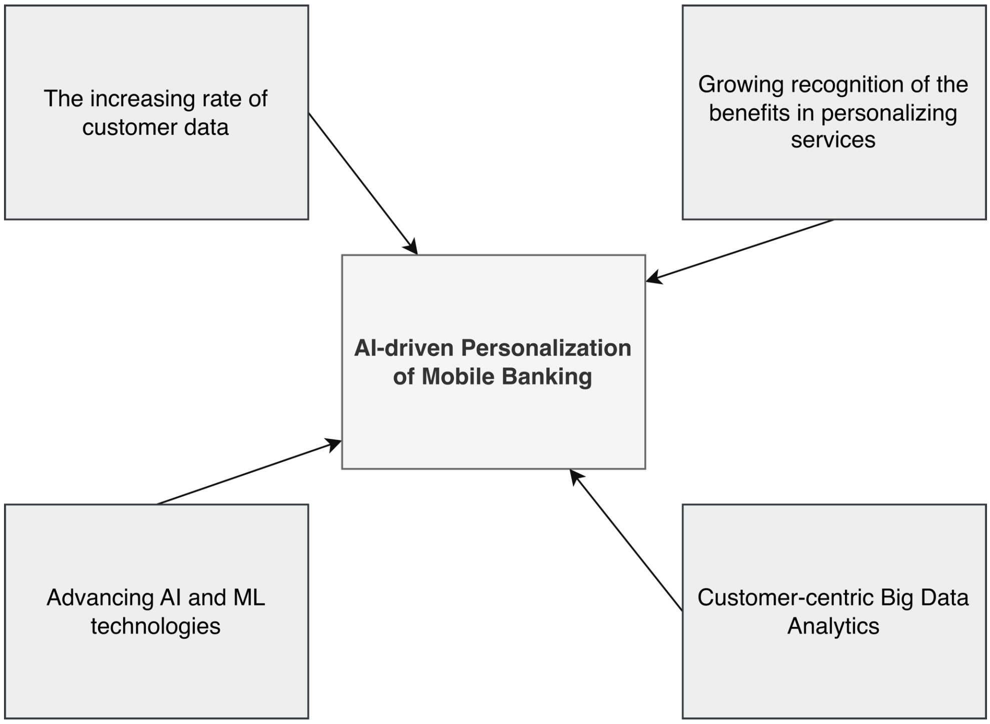

Figure 2. AI-driven Personalization of Mobile Banking
Source: Author's diagram

3 Machine Learning Algorithms for Personalized Mobile Banking

Machine learning is rapidly expanding its reach across various domains and applications (Osisanwo et al., 2017). As discussed in Chapter 2, advancements in AI and ML are primarily fuelled by the convergence of cost-effective computing power and the ability to capture and store diverse data, leading to an abundance of data that drives algorithm development and theoretical underpinnings (Hu et al., 2021). These factors drive the development of algorithms and theoretical foundations (Jordan & Mitchell, 2015).

According to Jordan & Mitchell (2015), machine learning stands out as a superior method for AI systems development. The shift towards training AI systems using machine learning, training a system e.g., with combinations of desired input-output is a significant step forward in AI development, offering several advantages over manual programming. This paradigm shift has consistently proven its efficacy in a multitude of real-world applications.

In banking, machine learning is seen as a key tool to improve operations and operational efficiency (González-Carrasco et al., 2019). In addition to operations, machine learning is extensively applied in other various banking areas, including personalization, automation, mobile banking, and robotic process automation (Donepudi, 2017). Machine learning is also promising since machine learning segments can update in real-time, enabling banks to automate personalization (Dawood et al., 2019). More specifically, and in addition to updating in real time, banks employ machine learning techniques for customer segmentation, recommendation systems, and personalized marketing campaigns based on data-driven decision-making (Singh et al., 2023).

However, in the banking environment, deploying machine learning models poses a challenge: finding a balance between predictive power and interpretability. While interpretable models facilitate a better understanding of input-output relationships, they do not necessarily achieve the same level of accuracy. This dual objective proves to be a challenging task (Hu et al., 2021). Various types of machine learning algorithms exist, each tailored to address specific types of problems. Although this categorization is evolving as new algorithms and implementations are developed, machine learning algorithms are typically categorized into three baskets (Osisanwo et al., 2017). These are:

1) Supervised learning algorithms

2) Unsupervised learning algorithms

3) Reinforcement learning algorithms

In addition to the three "main" categories, a common approach in real-world applications is to use hybrid machine learning algorithms that combine e.g., supervised, and unsupervised algorithms and/or modified versions overall of the algorithms to improve their accuracy. An illustrative case in banking comes from the study by Machado and Karray (2022), revealing that hybrid machine learning algorithms surpassed individual supervised counterparts in predicting credit scores for commercial customers. Although hybrids are extensively used in real-world applications, it is beneficial to also examine these algorithms individually.

Consequently, we will concentrate on a single exemplar algorithm from each of the three categories mentioned earlier: supervised, unsupervised, and reinforcement learning. This approach allows us to provide a comprehensive overview of the potential applications and challenges of each algorithm with adequate depth while adhering to the thesis's concise format.

3.1 Supervised learning algorithms

According to Diksha et al. (2022), supervised machine learning (SML) algorithms work in such a way that the machine leverages labelled data to train and predict outcomes in new scenarios. SML algorithms are widely used across diverse environments. The core idea is to approximate a function mapping input data (x) to an output (y) based on labelled data consisting of paired examples (x, y). Even though the core idea for SML algorithms is simple, they handle a broad range of input data (x) from vectors to more complex objects. SML algorithms utilize learned mappings (e.g., f(x)) de-rived from trained, labelled data to make predictions. While these algorithms share this same approach they do vary and find prevalence in certain applications over others (Jordan & Mitchell, 2015).

In banking, SML algorithms have been gaining prominence. These algorithms reshaping the decision making for loan and credit approvals, detecting fraud, forecasting, and analysing various types of data in text format. (Hu et al., 2021). Banks also employ supervised learning algorithms to analyse mobile banking data and enhance churn prediction models utilization common algorithms such as KNN, SVM, Decision Tree, and Random Forest (Rahman & Kumar, 2020). To better understand how SML algorithms are used to personalize mobile banking services, we will delve into K-Nearest Neighbors (KNN) which is one of the simplest machine learning algorithms and commonly used for classification applications (Sarker, I. H., et al., 2019). We will examine its applications, opportunities, and challenges within banking and project them into the mobile banking environment.

K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a classification model widely used in statistical pattern recognition (Laaksonen & Oja, 1996). Classification is a widely used machine learning technique that predicts the class of new data points based on a model trained on existing data (Sarker, I. H., et al., 2019). KNN represents each class with prototypes from a training set and assigns a class label to an unknown vector by majority vote among its k nearest neighbours, favouring an odd number for k's input variable to resolve any overlaps. Despite its simplicity, KNN is highly effective, demonstrating low error rates in practical applications (Laaksonen & Oja, 1996).

The model works by identifying the top k neighbours based on similarity in relevant attributes and characteristics (Mobasher et al., 2001). It categorizes new data points by measuring distances to existing ones with the chosen distance function and assigns them to the majority class among their k nearest neighbours, assuming they share the same class. For measuring distances to trained data points, the Euclidean distance is a commonly used distance function in the KNN algorithm. Other common distance functions, as found in the literature, include the Manhattan distance and the Chebyshev distance (Carbo-Valverde et al., 2020). KNN is a simple instance-based learning algorithm that is not based on complex mathematical models making KNN easier to apply in different domains (Adeniyi et al., 2016). In addition to class assumptions, it fundamentally assumes that all instances can be effectively represented as data points within an n-dimensional space (Mitchell, T. M., 1997).

In the context of banking, KNN can e.g., group customers into advanced segments with similar banking behaviours or preferences (Carbo-Valverde et al., 2020). For banks, leveraging this type of segmentation for customer profiling could be highly valuable as this enables banks to create targeted marketing initiatives, product suggestions, and refine services to align closely with the needs of each customer segment. This strategic personalization not only has potential to augment the mobile banking experience but also serves as a driver of profitability, as detailed by Dawood et al. (2019).

In addition to segmentation, the research conducted by Adeniyi et al. (2016) makes it clear that KNN could be promising for personalizing the mobile banking experience. In this research it was explored how a KNN classification method can be utilized for developing automated web usage data mining and recommendation systems. KNN was shown to be effective in improving navigational aspects, enhancing the user experience, and making accurate recommendations based also on user’s current preferences rather than basing the recommendations solely on the user’s previous usage history.

Amazon's use of AI algorithms such as KNN to predict customer behaviour and personalize product recommendations are also reflective examples of how AI and machine learning algorithms such as KNN can enhance customer experiences and improve conversion rates (Tong et al., 2020). In banking, the KNN algorithm also extends beyond personalization, as Rjoub et al. (2023) demonstrated. For instance, their study revealed that advanced variations of the KNN algorithm can be effectively employed to improve financial processes and enhance the security of banking and mobile banking applications.

Despite these factors, the use of KNN in personalized mobile banking presents its own challenges. Scalability and complexity issues in terms of computation may arise due to a high level of dimensionality and large volume of data in mobile banking platforms. In other words, depending on the dataset size and dimensionality, performance of KNN might not be sufficient in many cases so it's crucial for implementers such as banks to explore techniques to enhance KNN's efficiency and scalability for large datasets (Zhang, S., 2020). Rjoub et al. (2023) supports this argument as they emphasize that KNN methods can impose significant computational demands on financial institutions and data privacy in terms of implementing KNN also poses a challenge. Data privacy is crucial in mobile banking, as noted by Albashrawi and Motiwalla (2019) and with KNN's reliance on data proximity this may raise concerns about cybersecurity.

Another concern in the aspect of implementing KNN methods to personalize the mobile banking experience is the algorithm's sensitivity to misclassification costs, which necessitates a risk-adverse balance between minimizing false positives and false negatives (Zhang, S., 2020). In the context of personalized mobile banking with the use of KNN, misclassifying and failing to place a customer to relevant segment based on preferences or behaviour, as well as failing to understand the customer can lead to customer dissatisfaction due to misidentification (Chaban, M., 2021).

3.2 Unsupervised learning algorithms

Unsupervised learning methods, unlike their supervised counterparts that rely on labelled data, have the capability to derive meaningful patterns and insights from unlabelled data (Hastie, T. et al., 2009; Bao et al., 2019), making them more efficient but also cost-effective (Chiu et al., 2021). The utilization of unsupervised machine learning algorithms can therefore uncover patterns from unlabelled data that are hidden (Diksha et al. (2022).

Unsupervised learning algorithms also have an important role for personalizing and optimizing mobile banking services. These algorithms allow banks to process vast amounts of user data, including transaction history, behaviour patterns, and preferences, without the need for explicit labelling. By applying techniques such as clustering and dimensionality reduction, unsupervised learning algorithms can also be used to identify groups of similar users and segment them based on their banking behaviours (Chiu et al., 2021). This is especially relevant for mobile banking, since banks have highly dimensional data due to diverse sets of transaction and customer data (He et al., 2023).

Without further introduction, we will assess the K-means algorithm in a similar way based on literature.

K-Means

The K-means algorithm is a data partitioning/clustering technique that divides large datasets into non-overlapping, similar subsets (Papamichail, G. P., & Papamichail, D. P, 2007). It is an unsupervised machine learning algorithm which groups data points into a predefined number of clusters. The data points or data objects are grouped into clusters based on their similarity – objects within a cluster exhibit common characteristics or attributes that make them similar to each other, distinguishing them from objects in other clusters (Dawood et al., 2019).

AWC (Average Within Cluster) distance and DBI (Davies-Bouldin Index) are common metrics for assessing customer segmentation quality. AWC calculates the average distance within clusters, indicating their cohesion or tightness. Whereas DBI measures cluster separation, aiming for distinctiveness and minimized overlap. Both metrics can help businesses understand their customer segmentation and understand their preferences (Aryuni et al., 2018), which is crucial for personalizing digital banking (Wells et al., 2000).

The K-means range algorithm empowers customers by helping customers themselves in forming their product and service preferences across different attributes. (Papamichail, G. P., & Papamichail, D. P, 2007). This also gives control for customers in terms of the level of personalization which is considered critical in the context of mobile banking co-value creation between banks and their customers (Huang & Lin, 2005). After retrieving a set of relevant products, users can compare them based on various attributes simultaneously, aligning with their preferences and leading to more informed and satisfactory decisions (Papamichail, G. P., & Papamichail, D. P, 2007).

K-means clustering stands out also as a robust algorithm for clustering customers. Profiling customers by utilizing the K-means algorithm may help banks group customers into distinct segments based on more abstract attributes such as less conventional characteristics and behaviours. This ability opens possibilities for banks to automate personalized marketing campaigns and customer experiences (Dawood et al., 2019). Aryauni et al.'s (2018) research study also demonstrates the K-means algorithm's potential in driving the success of targeted marketing and personalized customer service.

An example of using this type of clustering along with other machine learning techniques and the utilization of big data to personalize customer experiences is a prominent Taiwanese bank referred anonymously in a case study by He et. al (2023), as "A-bank". Each month, customers of A-bank were automatically assessed and clustered based on their preferences and behaviour. This information was then synchronized across banking systems and departments, enabling personalized interactions with customers. This strategy also involved the mentioned clustering using machine learning and product affinity predictions, enabling the bank to offer customized product recommendations. The results showed a significant increase in A-bank's customer response rates and sales.

In addition to the possibilities of clustering in (mobile) banking, it's important to note that when such clustering is employed with a machine learning algorithm such as K-means, it introduces its own set of limitations and difficulties. According to He et al. (2023), clustering customers is not an easy task in banking due to large sets of data and high dimensionality. High-dimensional problems pose challenges not only in unsupervised but also in supervised machine learning, as observed by Hastie et al. in 2009. Moreover, unlike supervised learning algorithms, which can be assessed based on prediction accuracy, evaluating unsupervised learning methods is more complex. It often necessitates the use of domain-specific metrics or qualitative assessments which complicates the integration process. Therefore, evaluating the performance of unsupervised learning methods is more complex compared to their supervised counterparts with prediction accuracy serving as a robust metric. (Hastie et al., 2009).

The study conducted by Dawood et al. in 2019 highlights that this type of clustering can be effectively used for customer profiling in individual retail banks to understand their customers better. This is also due to these banks having continuous streams of high-volume data. K-means clustering in this environment can therefore be particularly effective, especially when used in conjunction with supervised algorithms, emphasizing the potential of hybrid machine learning approaches. This research underscores the effectiveness of a hybrid model combining K-means clustering for accurate bank customer profiling.

In the field of personalized mobile banking, the research conducted by Cui et al. (2021) in their paper "An Intelligent Optimization Method of E-commerce Product Marketing" also provides valuable insights for the implementation of K-means clustering. It demonstrates its effectiveness in segmenting digital customers based on perceived value. This finding suggests that K-means clustering can be applied in retail banking in a similar manner to categorize customers into e.g., high-value, medium-value, and low-value segments. In the context of banking, variables for segmentation could include risk profile, demographics, customer lifetime value, and several other metrics that are considered the most relevant, as banking data is very multi-dimensional (He et al., 2023).

3.3 Reinforced learning algorithms

Reinforcement learning (RL) is distinct from supervised and unsupervised learning, as it relies on environmental feedback, not explicit guidance. Its primary applications are in intelligent control and robotics (Qiang et al., 2011). Reinforcement learning models and agent-based modelling are increasingly being employed to optimize marketing strategies, particularly relevant in personalization efforts (Vargas-Pérez et al., 2023) making RL models relevant for context of this study into mobile banking. As Fu et al. (2006) outlined in their research of reinforced learning, agents are entities that navigate their surroundings by continuously evaluating and selecting the most appropriate actions in response to evolving conditions. These entities strive to optimize their choices to achieve desired objectives, maximize rewards, or minimize costs within the environment they operate in.

The agents engage in a cyclical process of observing, acting, receiving feedback, and updating its internal knowledge, continuously interacting with its environment. In other words, the environment operates like a carrot-and-stick situation, providing the agent with either rewards (the "carrot") for beneficial actions or penalties (the "stick") for detrimental ones. This feedback can range from e.g., numeric rewards to evaluations more intricate. This is the core idea, encouraging the agent to adapt and maximize rewards through learning (Qi-ang et al., 2011).

Q-learning

By implementing reinforcement learning in personalization efforts, particularly Q-learning, the system continuously adapts and enhances its personalization, dynamically responding to user interactions over time. This adaptability is essential for seamlessly accommodating evolving user needs and preferences (Ferretti et al., 2016). Deloitte (2011) also states that these preferences and needs are constantly changing, supporting the importance adaptive technology.

The study by Vlachogiannis and Hatziargyriou (2004) underscores the remarkable effectiveness of reinforcement learning algorithms, particularly Q-learning, in navigating the complexities of system optimization. It showcases the ability of these algorithms to uncover optimal control configurations while maintaining system stability, adhering to rigid constraints, and seamlessly handling multiple objectives to optimize. This evidence holds promising implications for the domain of machine learning algorithms employed in mobile banking personalization. It is worth noting that personalization overall is a multifaceted and abstract concept, where personalized recommendations represent just one facet, yet even within this subcategory, it manifests as a complex multi-objective optimization problem such as accuracy and diversity (Zuo et al., 2015).

In practice, Q-learning and reinforced learning algorithms in general appear to be promising candidates for implementation in mobile banking. As Taghipour and Kardan (2008) demonstrated, the effectiveness of Q-learning in developing a hybrid web recommender system showcases as effective for making informed recommendations and has been the foundation for making web recommendations. A study by Ferretti et al. (2016) supports this as it suggests that reinforcement learning, especially Q-learning, is a compelling approach to web personalization, particularly in tailoring the user interface and the user experience.

By learning from past experiences and optimizing actions based on their outcomes, reinforcement learning such as Q-learning, enables agents to make more informed marketing decisions, ultimately leading to the agents optimizing for desired outcomes such as maximizing return on investments (ROI) (Vargas-Pérez et al., 2023). This has the potential to develop personalized and new mobile banking solutions e.g., through A/B split tests by enabling reinforcement learning agents to optimize key metrics such as conversion rates for financial products and services.

However, the slow rate of learning and the need for coordinating multiple agents calls for further advancements in RL. In the implemented environment, Q-learning relies on a single state-action Q-table, making it hard to coordinate actions among these agents (Taghipour and Kardan (2008). In addition to the coordination problem, storing and updating Q-values for all possible state-action pairs is also impractical. In addition to impracticality, the traditional Q-learning model would not be effective in environments with several states because storing and updating Q-values for all possible state-action pairs is impractical and computationally expensive. (Bui et al., 2019). Therefore, hybrid models may offer a more efficient approach to personalized mobile banking due to the vast number of potential state-action pairs generated by complex recommendation algorithms as highlighted by Bui et al. (2019).

4 Findings

The aim is to critically evaluate the academic value of the work by presenting the obtained insights and supporting these findings with compelling arguments. In addition, the significance of the findings is evaluated and in the next chapter, the credibility of the research studies and my thesis are both assessed.

The evolution of personalized and especially AI-driven mobile banking is shown to be driven by four key factors, as explored in Chapter 2. Firstly, the increased availability of customer data plays a significant, yet overlapping role with the other key factors presented. Digital interaction keeps on increasing and so does the amount of data available for banks to analyse, enabling a deeper understanding of customer needs.

Secondly, advancements in AI and ML technologies have been instrumental, offering sophisticated tools for data analysis and personalization. Thirdly, there's a growing recognition of personalization benefits in the banking sector. This is evident in the rising demand and expectations from both banks and customers for personalized services. Lastly, the role of customer-centric big data analytics has become increasingly significant in banking. This approach to analytics allows banks to tailor their services effectively to individual customer needs, enhancing the overall customer experience. Collectively, these drivers highlight the transformative impact of AI and machine learning on personalizing mobile banking and shaping a more customer-focused approach in the industry.

Machine learning algorithms are important for various aspects of mobile banking, such as classifying customers, personalizing user interfaces and identifying distinct customer segments based on their preferences and behaviour. They also play a key role in refining marketing strategies, thereby significantly improving customer engagement. Hybrid and modified machine learning models, which aim to tackle the limitations and disadvantages of traditional algorithms, may also merge as superior choices for personalization in mobile banking. These advanced models combine the strengths of different machine learning algorithms to deliver personalized recommendations, tailored campaigns, and optimized customer experiences, driving increased engagement, satisfaction, and loyalty. By implementing hybrid machine learning models, banks may elevate their mobile banking experience and tackle scalability issues in terms of personalization.

However, it should be noted within this context that developing and employing highly complex models is not a simple solution. As highlighted by Hu et al. (2021), banks have the challenge of balancing accuracy and interpretability when developing or choosing these machine learning models. A study by Yoganarasimhan (2020) introduces another trade-off in the integration of machine learning - complex models still face trade-offs between accuracy and efficiency.

Typically, higher accuracy in machine learning models is achieved through complex algorithms that diversely assess patterns and multiple variables related to the user's history, characteristics, behaviour, and preferences. Yet, for these models to be viable in real-time applications, they must also be efficient which means it's also important to minimize computational load to ensure quicker processing. The challenge, therefore, lies in developing models that are accurate enough for personalization, while simultaneously being efficient for real-time operation.

5 Discussion and conclusions

This chapter aims to conclude the research and respond to the research questions that guided the investigation in this thesis. We critically evaluate how the integration of AI and machine learning in personalized mobile banking aligns with, and adds to, existing academic research. As such, our focus will once again centre on exploring the opportunities and challenges associated with AI-driven personalization and the integration of machine learning algorithms into (mobile) banking.

5.1 Implications to research

This thesis presents a critical evaluation of the integration of AI and machine learning in personalized mobile banking, highlighting the academic value and significance of its findings in relation to existing research. The importance of customer demographics, behaviour, and preferences in personalization efforts are also highlighted for improving user engagement, loyalty, and satisfaction within the mobile banking landscape. This aligns with previous studies, such as Dawood et al. (2019), which emphasizes the need for tailored personalization strategies. Overall, these strategies are crucial for fostering a positive user experience and facilitating co-value creation between customers and banks.

However, personalisation cannot be considered in isolation. As Laukkanen (2016) observed, it is necessary to adopt a holistic approach that combines personalisation with key factors such as user-friendliness, perceived value, and convenience. This holistic approach is essential not only for the successful adoption of mobile banking, but also for the personalization of mobile banking.

Furthermore, this thesis explores the transformative impact of machine learning algorithms in (mobile) banking, particularly in areas such as customer classification, user interface personalization, and customer segmentation. It suggests that hybrid and modified machine learning models, which combine various algorithmic strengths, are likely to emerge as superior choices for personalization in mobile banking. These advanced models can provide personalized recommendations and optimized customer experiences, thus driving increased engagement, satisfaction, and loyalty. However, this thesis also points out the challenges in developing and employing these complex models. In line with Hu et al. (2021) and Yoganarasimhan (2020), it notes the trade-offs between accuracy and efficiency in machine learning models. The challenge lies in developing models that are not only accurate but also efficient for real-time operation.

In conclusion, the thesis advocates for a comprehensive approach in integrating personalization into mobile banking platforms, emphasizing the need to balance advanced personalization features with user-friendly and seamless interface design. This balance may not be easy to reach yet crucial to ensure user satisfaction and continued usage of mobile banking services, as discussed by Manser Payne et al. (2021) and Schiaffino S. & Amandi A. (2004).

5.2 Implications to practice

The implications for practice are similar to the ones introduced in the previous sub-chapter as this thesis focuses on assessing opportunities and challenges inherent in real-world applications. In practice, the findings of this study suggest that financial institutions should prioritize integrating personalization with overall user experience, aligning with insights from Dawood et al. (2019) and Manser Payne et al. (2021). This involves seamlessly blending personalization strategies with user interface elements to ensure ease of use, perceived value, and convenience, which are crucial for enhancing customer satisfaction and fostering the adoption of mobile banking. In addition, financial institutions should focus on leveraging customer data analytics for personalization, drawing insights about customer behaviours and preferences to tailor services and product offerings (Noreen et al., 2023). Balancing personalization efforts with privacy concerns is also essential, ensuring adherence to data protection regulations and security measures to preserve customer trust, as noted by Wind (2001).

In addition, user-centred design ensures that advanced personalization features enhance rather than compromise the usability of mobile banking applications (Schiaffino S. & Amandi A., 2004). The integration of such AI-driven personalization features is not an easy task due to requiring extensive technical expertise and capability. Banks lacking such deep technical expertise and ability can benefit from working with an IT consulting or fintech firm, as it offers a viable alternative to developing and integrating AI-based personalisation strategies and models in-house.

5.3 Limitations and future research

Despite the comprehensive analysis and insights presented in this thesis, it is important to acknowledge the limitations that may affect the generalizability and applicability of the findings. Previous studies have heavily focused on the adoption of mobile banking, while personalized mobile banking represents a more advanced stage, suggesting that mobile banking research is still in its early stages in this regard which also is represented in the lack of extensive research in this area. These limitations therefore stem from the scope of the study, the early state of AI-driven mobile banking (AIMB) development, the evolving nature of AI and ML, and the inherent challenges associated with the research methodology.

The study's conclusions rely on the availability and quality of data pertaining to the utilization of AI and ML in mobile banking personalization. Limitations of the data, such as incomplete or insufficient data, may have compromised the accuracy and thoroughness of the analysis. Furthermore, the chosen methodologies and study scope are not intended to capture the entirety of the intricate landscape of AI personalization practices; rather, the opportunities and challenges with exploring ML implementation. These factors may therefore affect the coverage of the results.

In addition, the technologies, strategies, and models used for personalisation are often confidential to banks, which makes it ultimately challenging to analyse them in depth and link the analysis into the mobile banking environment since this development is still being in the early stages. Integrating multiple perspectives is also a major challenge. Essential aspects such as banking, marketing, AI, machine learning and user experience all play a crucial role and need to be considered holistically. These perspectives add complexity and impose limitations on the depth and breadth of analysis, pointing to potential areas and deeper analysis for further research in the field.

Furthermore, the field of AI is constantly evolving, with new advancements and applications emerging rapidly. Therefore, the findings of this study may be limited to the current potential and state of ML in (mobile) banking personalization. Due to this ever-evolving nature of AI and machine learning, further research is most likely necessary to incorporate the latest developments and assess their impact on the field.

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