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# Commercial Bank Investment Patterns: Trends, Challenges and Opportunities

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**Abstract**
In business and society at large, artificial intelligence (AI) has attracted a lot of interest, especially in the banking industry. Although artificial intelligence (AI) has shown promise in investment banking and backend operations, its potential in commercial banking particularly in customer-facing services remains untapped. In order to fill this vacuum, this study identifies the existing uses of artificial intelligence (AI) in commercial banks as well as the difficulties in putting these uses into practice through an organised examination of the literature. According to our research, artificial intelligence (AI) has a number of benefits for commercial banks, such as decreased loan losses, increased payment processing security, job automation for compliance, and better client targeting. But there are obstacles to overcome when integrating AI into commercial banking procedures. These include maximising technology gains, successfully integrating AI into current business procedures, and guaranteeing user acceptability while upholding privacy, openness, and sufficient documentation. These difficulties highlight how behavioural finance research has to be expanded in order to fully comprehend how AI may be used to improve consumer relations and operational procedures. In order to progress artificial intelligence (AI) in commercial banking and its consequences for behavioural finance, the suggested research agenda attempts to investigate these prospects and tackle the associated difficulties.

**Keywords:** Artificial Intelligence, AI Implementation, commercial banking, customer interaction, behavioral finance

## 1. Introduction

The digitisation tsunami, along with developments in data analytics, creates significant opportunity for businesses across industries. Many organisations have effectively used AI to improve operations and even reinvent business models. Regardless of these achievements, the use of AI in Financial transactions has mostly been limited to a select group of backend products and services, which include credit scoring by credit card companies or stock prediction and credit rating in large investment banks-domains that have historically been dominated by highly developed computational algorithms. Conversely, surprisingly less focus has been placed on AI applications that involve direct communication with customers, which are essential to commercial banking. Commercial financial institutions have not yet completely explored the possibilities of artificial intelligence in these areas, while prioritising client involvement in funding, settlement of payments, and asset collecting.

Financial risk is the unpredictability of returns' variation or fluctuation. There are a variety of financial risk kinds. These hazards have a detrimental effect on an organization's financial performance. A variety of financing risks, such as those associated with corporate default risk loans, can be broadly referred to as financial risks. Potential stock market drops resulting from asset variable volatility give rise to financial risk. This is typically linked to debt and the likelihood that obligations and liabilities cannot be balanced against available resource. A company's capacity to carry out plans and make crucial decisions in order to achieve its objectives and generate high returns is reflected in its financial success. This absence is especially troubling because emerging, tech-savvy rivals are putting more and more pressure on commercial banks. If commercial banks do not adjust to the increasing competition, McKinsey predicts that revenue decreases of 10% to 40% might occur by 2025 in major revenue-generating areas, including retail payments, as well as mortgages, SME loans, and consumer financing. These sectors are crucial to commercial banks' conventional business models, and their integration with AI might put them at danger.

Furthermore, there is a discernible deficiency for studies on AI pertaining to the fundamental operations of commercial banks. Despite a number of literature articles (Bahrammirzaee, 2010) [16] examine AI in banking, none fully cover all important commercial banking and financial sectors. In order to close this gap, we suggest the following studies. Investigated Pakistani listed companies' working capital practices. Their results suggest that Pakistani company managers are following a conservative Work Cycle Management (WCM) approach, as seen by the early payment to creditors and the delayed collection of monies from debtors. Thus, they recommend that in order to improve company performance, Pakistani financial managers should shorten their cash conversion cycle. The working capital practices of listed Pakistani companies are determined by both external and internal variables, as investigated by Nazir and Afza (2009a, b). The empirical data indicates that internal factors that have a major impact on an organization's WCM procedures include the operating cycle, return on investment, and Tobin's q. On the other hand, the primary extrinsic reason explaining the WCM guidelines for Pakistani businesses. A more recent research investigation by Wang *et al*. (2020) reveals that a shift in the corresponding life cycle stage also has an impact on Pakistani enterprises' working capital practices. As a result, compared to growing or established businesses, start-ups had distinct financing needs.

## 2. Theoretical Background

### 2.1. Commercial Banks' Principal Business Segments

Four primary variable set commercial banks apart: the services and goods they provide, the business ventures they undertake, the clientele they cater to, and the effects these elements have on client relationships.

Adoption of AI has the ability to improve each of these fundamental areas. Precise evaluation of the solvency of its customers is essential for financial institutions to provide profitable loans. When processing payments, banks must maintain the security, functionality, and upkeep of their payment infrastructure, which includes electronic currencies and Kiosks for cash withdrawals. Commercial banks now have significant data on consumer spending patterns thanks to the rise in payments that are not in cash in recent decades. Commercial banks operate primarily based on lending, deposits, and payment processing, but two other areas are equally vital to their business.

Commercial banks must first strictly abide by all applicable regulations and rules. They are subject to some banking-specific rules and regulations, including the Payment Facilities regulations (European Commission, 2015) that affects all organizations that provide solutions for payment and the Basel Accords (Bank for International Settlements, 2017) [17], which place restrictions on giving activities. These regulatory obligations have a substantial impact on the amount of risk large financial institutions can take on and how they operate. Second, commercial banks need to offer and market their goods and services to clients in an efficient manner. In this situation, managing Client Relationships (CRM) is difficult since the items that various commercial banks provide are frequently comparable. Consequently, accurate client targeting turns into a vital component of commercial banking success. An excellent approach to do this is by managing customer connections well.

### 2.2 Commercial Bank Information Systems

Information systems (IS) have been introduced during the past few decades, and banks and their clients have benefited greatly from this. Point out that improved business procedures and services have resulted from IS in commercial banking. The capacity for clients to do internet and card-based transactions, as well as monitor their accounts online, is one major development made possible by is (Krueger & Leibold, 2008). A client-server architecture that stores customer data and account information on central servers and makes it available to consumers online supports these features. Commercial software programs, such SAP's "Commercial Banking Operations" module (SAP, 2019a), are extensively accessible in the lending industry. CRM technology also make it easier for commercial banks and their clients to communicate.

### 2.3. The Inception of a Novel Information Systems Wave

In previous years, the financial sector was greatly impacted by the advent of new information systems (IS), especially in the field of mathematical finance, as noted by Seese, Weinhardt, and Schlottmann (2008). But newer technological developments have brought even more potent breakthroughs that are changing the IS environment. Artificial intelligence (AI) has gained prominence due to the growing availability of data and the decreasing cost of processing power, making it possible to tackle increasingly difficult and complicated jobs. Even with its increasing significance, artificial intelligence (AI) is not well defined in the literature, and there is still constant discussion over the idea. An innovative gathering that was centred on one of the initial ideas for the Dartmouth ConferenceIn a seminal work on artificial intelligence, the late John McCarthy and associates (1955) said that they were studying "instruments that can be made to simulate [Intelligence]".

Later, AI is defined by Russell and Norvig (2013) as the study of intelligent agents that are able to act on their own. Huang *et al*. (2004) state that the unique feature of artificial intelligence (AI) is its capacity to generate models from the underlying structure of data, without the need for specific guidance regarding which information to search for or how to behave. The current spike in enthusiasm about AI presents another challenge. Even though "data mining" and "machine learning" are separate and independent ideas, the phrases "AI" as "machine learning" are frequently used synonymously. Comparison for improving understanding of AI is with econometric techniques. Econometric models provide rational answers to a wide range of issues, but they are not the same as artificial intelligence.

### 2.4. Reasons for Applying AI to Commercial Banks and Present is Challenges

The conventional business models of commercial banks are under serious challenges from recent changes. Increasing competition, changing consumer tastes, growing regulatory demands, expanding security risks, and growing expenses associated with sustaining large branch and IT systems are some of these themes. For commercial banks, each of these elements brings opportunities as well as challenges.

#### 2.4.1 Increasing Level of Rivalry

Commercial banks have always benefited from market protection and regional supremacy. But the emergence of e-services and digital technologies has upended this established order. Observes that the financial marketplace is seeing increased competition due to the deregulation of the financial services industry and the broad use of new such as PayPal, Transfer Wisdom for converting currencies, and MyBank for credit supply. These fresh competitors are improving the efficacy, affordability, and productivity of their services. One such example involves the AI-powered Chinese lender MyBank. Nowadays, non-banking organizations are focussing on profitable banking services like PayPal payment processing.

#### 2.4.2 Modifying Client Preferences

The banking sector is being impacted by changing consumer preferences in addition to heightened competition. According to Jakšič and Marinč (2015), contemporary bank clients need more empowerment, continual connectedness, and interesting experiences. Customers are choosing banks that offer the most enticing possibilities because of the increased competition, which is eroding conventional bank-customer relationships. This is particularly true for those who are underserved by traditional banking, SMEs, and millennials.

These changing consumer habits provide chances as well as difficulties. Banks may use AI to better comprehend and interact with consumer behaviour. AI may assist banks in bettering their service offerings and customising their marketing campaigns by evaluating transaction data. Moreover, AI gives banks a chance to investigate how effectively their clientele embraces new technology. Innovative methods can beutilised to evaluate the effect and acceptability of AI applications in key banking domains.

#### 2.4.3 Growing Needs for Regulation

Banks are under a great deal more regulatory pressure now than before the previous financial crisis. More than 50,000 rules were imposed in G20 nations between 2009 and 2012, significantly increasing banks' operating expenses (Butler & O'Brien, 2019) [18]. Even for major institutions, complying with the amount of regulatory updates increased to nearly 50,000 in 2015, a 100% rise from 2012 (Butler & O'Brien, 2019) [18]. As such, the banking industry has emerged as one of the world's most regulated. The complexity is increased by the reliance on manual compliance procedures carried out by specialised specialists, who are sometimes challenging to find and train.

RegTech has come to light as a possible remedy for these problems. RegTech makes use of IT to help businesses in minimising legislative risks, implementing compliance systems and data administration, determining the effects on company models, policies, and procedures, and overseeing regulatory obligations through reports on compliance (Butler & O'Brien, 2019) [18]. In this field, artificial intelligence (AI) technologies are very helpful since they can automate repetitive processes, lower error among people, and let up resources. Regulators are already becoming more aware of and supportive of early AI-based RegTech implementations (Butler & O'Brien, 2019) [18].

#### 2.4.4 A Shift in Fraudsters' Behaviour

For banks, security continues to be a major concern. Conventional defences against fraud, such Secure Sockets Layer (SSL) encryption, are finding it difficult to stay up to date with new strategies. According to Jadhav *et al*. (2016) [19], the worldwide expense of credit card theft rose by 19% to $14 billion in 2016. Modern fraud strategies call for sophisticated defences, which is why banks are strengthening their security measures. AI has great potential to fight fraud by identifying changes in the criminals' behaviour. Kumar *et al*. (2018), for instance, detail an AI-based system intended to spot fraudulent activity aimed at senior citizens. These AI-driven solutions are working well for improving security measures and adjusting to new fraud tendencies.

#### 2.4.5 The Business Network's Scale

Another issue is the vast branch and IT network of banks. ATM network management and upkeep are expensive, and branch locations have a big impact on bank earnings (Zapranis & Alexandridis, 2009; Alfaro *et al*., 2019) [20, 13]. This network optimisation is essential to financial performance. AI has demonstrated promise in resolving these problems. Lázaro, Jiménez, and Takeda (2018) [36], for example, show how AI can automate the scheduling of cash delivery and collection for ATMs and branches. For instance, BBVA enhanced branch placement tactics with AI, which resulted in more income (Alfaro *et al*., 2019) [13]. These examples show how AI may enhance network management to maximise productivity and increase profitability.

## 3. Literature Review

The banking industry is no exception, with AI technologies showing great promise. For example, Banco Bilbao Vizcaya Argentaria (BBVA) in Spain has witnessed significant revenue, profitability, and cost savings because to AI-driven client targeting, optimised business processes, and smart branch network placements (Alfaro *et al*. 2019) [13]. According to Casu, Girardone, and Molyneux (2016), lending, deposit taking, and payment processing are the main priorities of the system and as the primary lenders to consumers and companies. RegTech (regulatory technology) solutions help banks internally handling problems with compliance (Butler & O'Brien, 2019) [18].

Clients now have additional choices for banking services, such as enquiries about loans, payment alternatives, and monitoring their accounts (Hormozi& Giles, 2004). According to Ískarsdóttir *et al*. (2018), the accuracy of forecasting customer defaults in micro lending is increased by combining the analysis of smartphone data such as call logs, text messages, and app usage with sociodemographic data.

## 4. Objectives

- To examine the challenges faced by commercial banks.
- To explore the opportunities available for commercial banks.

The approach described by Webster and Watson (2002) [21], which entails three crucial phases to develop a concept matrix for assessing academic literature, is followed in this structured literature review:

- Finding Appropriate Literature
- Review Structure
- Theoretical Advancement

### 4.1 Methodology

The study will adopt an exploratory research design to identify and understand the potential opportunities available for commercial banks in their investment strategies. This approach allows for a flexible and in-depth examination of emerging trends and innovative financial instruments. Review existing literature, including academic journals, industry reports, and case studies, to understand the current landscape of commercial bank investments and identify gaps where new opportunities may arise.

**Locating Applicable Writing**

The first step was looking through databases to find the best journals in the IS and Banking and Finance sectors based on the VHB-JOURQUAL 3 rating (VHB, 2015). The papers from three pertinent workshops centred on IS in the financial sector, as well as journals of high academic quality (A+ and A-rated), are included in this rank. Three more publications were chosen because they are relevant to machine learning and expert systems, guaranteeing that the focus is on high-caliber sources that are relevant to banking on business. There were restrictions on the quest to articles published between January 2009 and August 2019 to document the most recent scholarly debates to articles published between January 2009 and August 2019 to document the most recent scholarly debates. Using Rowley and Slack's (2004) building blocks technique, keywords for the search were created. The search was conducted using phrases like "artificial intelligence," "machine learning," and data mining to look for articles that were focused on finance. Terms like "option" and "stock prices" were removed with the goal to focus upon the outcomes and eliminate irrelevant content. This more comprehensive strategy sought to address new financial concerns that touch on AI. Seven combinations of key words were used in the search for computer science-related sources: "data mining" in conjunction with phrases like "bank", "the credit risk", "deposit", "payment processing", "money laundering", "RegTech", "compliance", and "customer relationship management". 337 papers were found to be possibly relevant by the first data base query. An abstract scan was performed under.

Webster and Watson's (2002) [21] technique in order to exclude unrelated works. The studies that applied AI within settings for commercial banking. Excluded from consideration were publications that discussed AI in relation to trading, portfolio management, systematic risks, macroeconomic concerns, game theory, or model optimisation. After this scan, 34 pertinent publications remained on the list. Ten additional pertinent publications were included after doing a forward-backward search in accordance with Webster and Watson's (2002) [21] advice. In the end, 44 papers were chosen for examination.

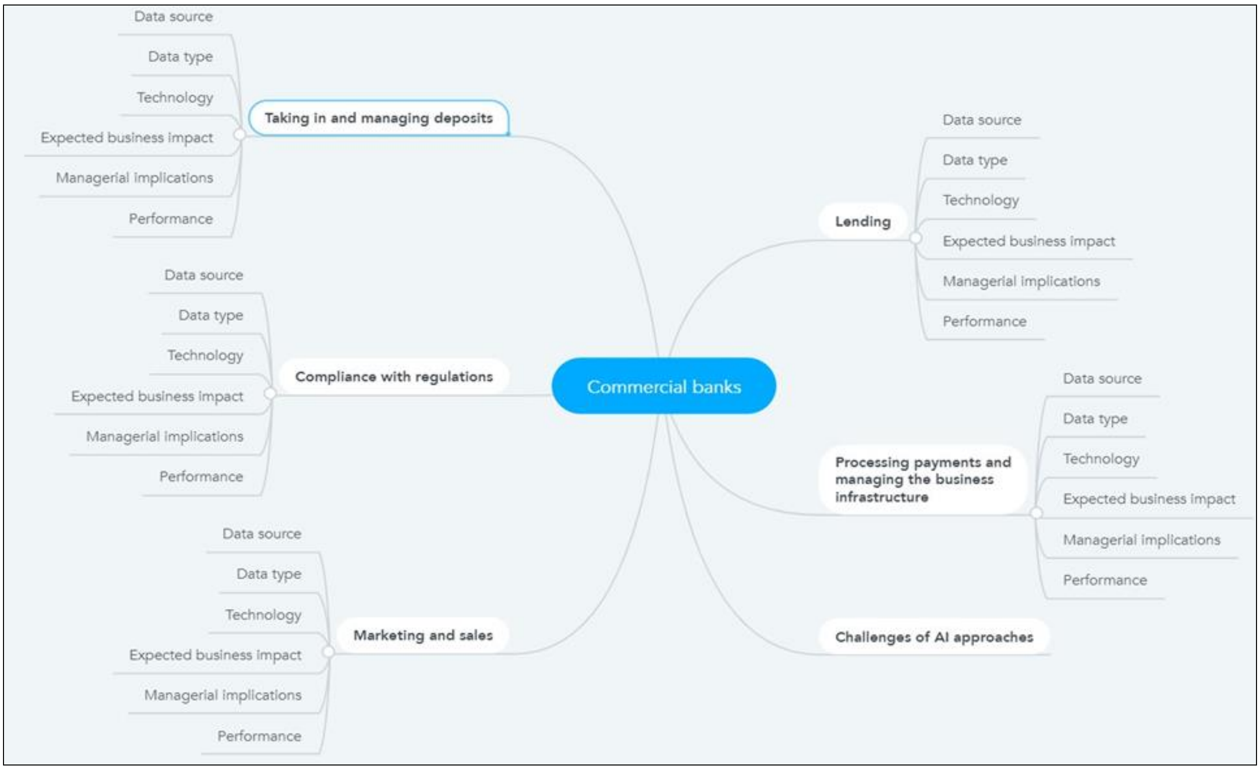


**Fig 1:** Key functions of commercial banks and their AI-driven impacts.

**4.2 Organising the Evaluation**

The review was arranged utilising a concept-centric methodology in the second stage. To ensure that the review focusses on concepts rather than specific writers, a concept matrix was built, following the guidelines provided by Webster and Watson (2002) [21]. In order to construct this matrix, important aspects pertinent to the subject are identified, and their treatment in the scholarly literature is examine

**4.3. Evolution Theoretical**

Using Patton's (2002) method as a guide, an iterative qualitative content analysis was carried out to find patterns in the literature. In order to identify recurrent themes and patterns among the articles, this method required frequently analysing the text. This repeated examination led to a continual refinement of the concept matrix. Lists the dimensions that were utilised to create the concept matrix.

## 5. Results Discussion

The review initially looks at the relationships between several commercial banking business sectors and "technology", "data source", "data type", "performance", "expected business impact", and "managerial implications". The article next provides an overview of the difficulties that have been reported in the literature when deploying AI in commercial banks.

### 5.1. AI-Powered Lending

AI has a big impact on lending from a commercial and technological standpoint. AI technology enables commercial banks to do two things: (1) utilise new algorithms to analyse client data; and (2) include previously unutilised data kinds to improve forecast accuracy. When it comes to business, artificial intelligence (AI) enhances credit risk assessments, which lowers losses for banks assessing credit cards, personal loans, or business loans.

#### 5.1.1 How Is AI Affecting Loans?

#### 5.1.1.1 Improved Forecasts Using Additional Data Types

The review emphasises how AI broadens the scope and diversity of data kinds that are utilised in credit risk evaluation. Predictive algorithms for loan default perform better when transaction data is included, according to a number of research (Tobback and Martens 2019; Kvamme *et al*. 2018; Khandani *et al*. 2010) [22, 23, 24]. According to Onay and Öztürk (2018) [25], commercial banks are undergoing a radical change as a result of integrating non-traditional data sources including social media, telecom, and utility bills.

Integrate sentiment ratings with financial measures using internal due diligence reports to forecast a Chinese lender's loan approval choices. Forecast credit card delinquencies with accuracy by combining credit bureau data with account-level credit card data. To predict SME defaults in Switzerland, use data on internet user behaviour, social media evaluations for SMEs, and conventional financial parameters. According to Brücker, van Kampen and Krämer (2013), credit risk assessment can be improved by incorporating data from rejected loan applications into models, while models that only use data from accepted applicants may be biassed. In the end, these research investigations show that adding a variety of kinds of data and sources improves the accuracy of predictions of credit risk models and offers useful signals for credit risk estimation (Khandani *et al*. 2010; Onay and Öztürk 2018) [25, 22].

#### 5.1.1.2 A wider range of algorithms for estimating credit risk

The implementation of several new algorithms further supports the improved capacity to provide reliable predictions using a variety of data kinds. In order to anticipate SME defaults, present an algorithm that combines credit bureau data, conventional firm and loan characteristics, internet user behaviour data (such as clicks and log-ins), and social media ratings. In order to estimate credit risk, neural networks have been employed extensively. Neural networks are utilised by Óskarsdóttir *et al*. (2018) [26] in their models. In addition, Óskarsdóttir *et al*. (2018) [26] use random forests in their data analysis based on smartphones. Support vector machines (SVM) are used by Tobback and Martens (2017) to analyse consumer transactions, while regression trees are used by Khandani, Kim, and Lo (2010) [22] to combine.

Credit bureau data, account balances, and customer activities are used to forecast credit card delinquencies. Using conventional customer data, Chen and Huang (2011) show how well artificial neural networks can forecast credit defaults. Kvamme *et al*. (2018) [23, 24] use convolutional neural networks to forecast mortgage defaults. Identify firms as risky or non-risky borrowers using an ensemble method that combines SVM with bagging and random subspace methods. Evaluate the creditworthiness of SMEs in Turkey using a multilayer perceptron, a different kind of neural network. List a number of AI algorithms that are used to examine financial accounts in order to spot fraud in their evaluation. Neural networks are used by Xiong *et al*. (2013) to evaluate credit card data and forecast individual bankruptcies. Decision trees and boosting algorithms are used by Chrzanowska, Alfaro [13] to predict mortgage defaults. Neural networks are used by Sarlija, Bensic and Zekic-Susac (2009) to analyse behavioural data from credit card bills to calculate the default timings. Provide a hybrid credit scoring model that combines logistic regression and artificial neural networks.This shows that AI is capable of handling data kinds that were not previously used in the loan environment. In addition to managing a variety of data formats, AI models outperform conventional techniques in estimating the credit risk of consumers. For example, Khandani *et al*. (2010) [24] point out that AI-based techniques typically outperform conventional models like discriminant analysis and logistic regression. In particular, demonstrate that, in comparison to decision trees and random forests, regression a popular model for credit risk estimation often has worse accuracy and recall as well as a greater false positive rate. Additionally, Brown and Mues (2012) [27] show that random forests perform better than more conventional models like logistic regression, especially when it comes to datasets with significant class imbalances like loans. Abellán and Castellano (2017) [11] examine several ensemble classifiers used in credit scoring, while Zurada (2010) evaluates the prediction abilities of many AI systems used in credit risk assessment. According to Zurada (2010), decision trees outperform alternative models in terms of both classification accuracy and interpretability. Genetic algorithms outperform a number of different techniques in the prediction of credit defaults, as demonstrated by Hens and Tiwari (2012). Compared to logistic regression-based segmentation, Bijak and Thomas (2012) [28] show that classification and regression tree (CART)-based segmentation produces more homogenous segments; nevertheless, this enhanced segmentation does not always translate into more accurate credit scores. On the other hand, discover that statistical models may sometimes outperform AI systems. For example, the Cox model can predict theduration of a loan till a borrower fails. In terms of credit scoring, Li *et al*. (2016) hybrid model performs better than logistic regression. But it's important to understand that there isn't a single algorithm that works best everywhere. Claim that the dataset used for training and testing affects the efficacy of various algorithms as well as the top-performing algorithm.

### 5.2. Using AI to manage company infrastructure and process payments

According to the studied literature, fraud detection and payment network scale management are two important areas where AI plays a significant role in payment processing. By finding trends in huge transaction datasets, Artificial Intelligence (AI) improves the detection of possibly fraudulent transactions. AI also enhances company infrastructure management through process optimization, ATM network utilization estimation, and bank branch placement optimization. Consequently, AI helps to ensure the safety and effective management of even large-scale corporate networks.

### 5.2.1. Strengthening payment network security

AI is significantly improving the security of commercial banks' payment systems in the critical area of fraud and money laundering detection. 2016 saw the rise of counterfeit cards $14 billion in payments were made worldwide and $7.1 billion in the US. In order to improve security, Kumar, Muckley, Pham, and Ryan (2018) [30] show that random forests and SVMs in conjunction with transactional data may identify instances of elderly exploitation. Zhang and Trubey (2018) identify money laundering by using transactional data and decision trees, random forests, SVMs, and artificial neural networks. According to Zhang and Trubey's (2018) research, machine learning neural networks exhibit optimal performance in scenarios with notable class imbalances and exhibit reduced sensitivity to changes in the intended variable's percentage. A genetic algorithm is used by Duman and Ozcelik (2011) [28] to identify phony credit card transactions at a Turkish bank. Strong predictive performance is demonstrated by the models of Kumar, Muckley, Pham, and Ryan (2018) [30], suggesting that these models have potential to increase monetary system security. The use of AI in identifying fraudulent activity in the internet for banking and money laundering in transactions is another area that Jadhav, He, and Jenkins (2016) [19] emphasize. They make reference to a mechanism that the US Treasury Department created to help banks identify fraud in cash transfers. Additionally, banks may use AI to identify money laundering in both Credit card statements, cash and electronic transactions, and financial statements. Nevertheless, their evaluation provides little insight into the algorithms' predictive capabilities and does not go into great detail about how creative the techniques.

### 5.2.2 Controlling the size of the infrastructure for businesses

There isn't much research on the subject of managing payment infrastructure with AI. In 2009, Zapranis and Alexandridis used neural networks to analyse a time series of end-of-day ATM balances in England in order to anticipate the amount of cash that would be taken out each day. Using neural networks, Serengil and Ozpinar (2019) [31] forecast cash flows at 6,500 ATMs in Turkey. Grozin, Natekin, and Knoll (2015) [32] use SVMs and random forests to forecast how much money will be needed in Russia to restock dispensers. Lázaro, Jiménez, and Takeda (2018) [36] go one step further and describe how to incorporate these forecasts into business operations in addition to giving a way to maximise the quantity of cash transferred to each branch. Herrera-Restrepo and colleagues (2016) assess bank branch efficiency using grouping based on centroid. They divide up the branches according to output-related parameters like the quantity of loans disbursed, as well as metrics like the number of full-time equivalent workers. The components of a Canadian bank are then profiled based on the clusters allocated to each branch, offering insights into branch performance and facilitating focused increases in operational efficiency.

Commercial banks (Grozin *et al*. 2015; Serengil and Ozpinar 2019) [32, 31], a national bank (Lázaro *et al*. 2018), and a conference organiser (Zapranis and Alexandridis 2009) [20] contributed the data that these writers utilised. In reality, obtaining and gathering enough data is not a big problem because commercial banks usually have complete access to information about their branches and ATMs.

## 6. A Behavioural Finance Research Agenda

An agenda for behavioural finance research is presented in this section. Research in behavioural finance usually focusses on one of two things: either individual behaviour or its consequences for financial market outcomes. Numerous research analysing the behavioural patterns of three primary groups customers, workers, and other stakeholders, such as regulators and auditors were covered in the preceding sections. Behavioural finance frequently investigates the effects of psychological characteristics on individual investors, including gender, preferences, and risk-taking inclinations as highlighted by Jackson (1976), as well as the 'Big Five' personality qualities outlined by Norman (1963). Additionally, it looks into how human biases like mental accounting and conservatism affect people's ability to make sound financial decisions and their overall well-being (Anic & Wallmeier, 2020; Brüggen *et al*., 2017) [33, 34]. Furthermore, this research investigates methods to reduce investors' behavioural biases, including using robotic advisers in wealth management, and looks at ways to make financial information more accessible to individual investors.

Important subjects in behavioural finance include consumer acceptance and desire to utilise new financial products, as well as the allure of complicated financial services (Anic & Wallmeier, 2020; Chiou & Shen, 2012; Jiménez & Díaz, 2019) [33, 35, 36]. For example, Chiou and Shen (2012) [35] examines drivers of online financial service adoption, whereas Jiménez and Díaz (2019) [36] investigate how characteristics including educational level, gender, self-employment status, and ATM usage impact the desire to utilise internet banking. Additionally, Brenner and Meyll (2020) [37] point out elements that are critical to the acceptability of robotic advisers.

Behavioural finance encompasses important domains such as the adoption and utilisation of novel financial instruments, especially intricate ones. Research such as that conducted by Chiou and Shen (2012) [35] examines the aspects that impact the uptake of internet banking and online financial services, respectively, while Brenner and Meyll (2020) [37] focusses on the characteristics that are essential for the acceptability of robotic advisers. In order to get insight into mental accounting, researchers may use artificial intelligence (AI) to analyse transactional data and examine how personality factors like Norman's "Big Five" affect financial decisions. With the rise of AI-powered financial products, it's critical to investigate what motivates users to use these services, whether they can trust AI judgements, and how best to present AI outcomes to users in a way that builds both attraction and confidence. Furthermore, the part that staff members play in client consultations, particularly in the context of growing AI use, emotionally charged scenarios should be redefined with an emphasis on how AI can support these interactions and striking a balance between human and AI decision-making.

## 7. Conclusion

This study emphasises how AI has broad applications across commercial banks' fundamental business functions. By evaluating hitherto unexplored data, artificial intelligence (AI) improves credit risk models in the lending industry, resulting in more precise forecasts, higher earnings, and the capacity to service additional clientele. AI's ability to detect fraud and stop money laundering enhances the security of payments, and its ability to forecast demand helps manage cash flow, which lowers operating expenses for branch networks and

ATMs. AI helps with compliance by digesting rules quickly, identifying questionable activity, and guaranteeing correct reporting. Additionally, AI-driven marketing and sales techniques may more effectively target clients with appropriate items; additionally, AI can lower costs and bring novel services in deposit and account management.

But achieving these advantages depends on tackling a number of obstacles. Ensuring legal compliance and model explain ability are essential for effective risk management with AI. AI can expedite compliance and improve marketing efficiency, but privacy issues need to be addressed. Although the integration process itself offers hurdles, integrating AI into corporate operations has the potential to result in more cost-effective infrastructure management. The evaluation also identified knowledge gaps regarding AI's application to payment processing and deposit management. Further research on AI's potential for comprehending investor behaviour, customer attractiveness to AI-based services, and AI-employee interaction is also necessary. To maximise the use of AI in banking, research should also concentrate on uses of AI outside of commercial banking, including knowledge from other industries.

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