

The Impact of Financial Technology Adoption on the Financial Performance of Banks in the Democratic Republic of Congo

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ABSTRACT

This study investigates the impact of financial technology, specifically agency banking and mobile money on the financial performance of commercial banks in the Democratic Republic of Congo (DRC) over the period from 2018 to 2023. In a context characterised by persistently low levels of financial inclusion, Congolese banks are increasingly adopting digital innovations. This research assesses whether such technological advancements contribute to measurable improvements in bank profitability.

Using a balanced panel dataset comprising twelve commercial banks, the study employs Return on Equity (ROE) as the primary dependent variable. Agency banking and mobile money serve as the key explanatory variables, while total assets and customer deposits are included as bank-level control variables. The econometric analysis is conducted using a random effects model.

The findings reveal that both agency banking and mobile money have a positive and statistically significant influence on ROE, suggesting that fintech adoption enhances bank profitability in the DRC. While total assets show a positive and significant effect, the customer deposits variable was found to be statistically insignificant, highlighting underlying structural inefficiencies within the sector.

The study concludes that fintech represents a viable strategy for improving bank performance and advancing financial inclusion in developing financial systems such as that of the DRC.

Keywords: Agency Banking, Mobile Money, Financial Performance, Return on Equity, Fintech, Democratic Republic of Congo.

ÖZ

Bu çalışma, 2018-2023 yılları arasında Demokratik Kongo Cumhuriyeti'ndeki (DKC) finansal teknolojinin, acente bankacılığı ve mobil paranın ticari bankaların finansal performansı üzerine etkisini araştırmaktadır. Finansal kapsayıcılığın sürekli olarak düşük seviyelerde seyrettiği bir bağlamda, Kongolu bankalar dijital yenilikleri giderek daha fazla benimsemektedir. Bu araştırma, bu tür teknolojik ilerlemelerin banka kârlılığında ölçülebilir iyileşmelere katkıda bulunup bulunmadığını değerlendirmektedir.

On iki ticari bankadan oluşan dengeli bir panel veri seti kullanan çalışma, birincil bağımlı değişken olarak Özkaynak Karlılığını (ROE) kullanmaktadır. Kurum bankacılığı ve mobil para temel açıklayıcı değişkenler olarak kullanılırken, toplam varlıklar ve müşteri mevduatları banka düzeyinde kontrol değişkenleri olarak dahil edilmiştir. Ekonometrik analiz rastgele etkiler modeli kullanılarak gerçekleştirilmiştir.

Bulgular, hem acente bankacılığının hem de mobil paranın ROE üzerinde pozitif ve istatistiksel olarak anlamlı bir etkiye sahip olduğunu ortaya koymakta, bu da DRC'de fintech benimsemesinin banka karlılığını artırdığını göstermektedir. Toplam varlıklar pozitif ve anlamlı bir etki gösterirken, müşteri mevduatları değişkeni istatistiksel olarak anlamsız bulunmuş ve sektördeki altta yatan yapısal verimsizlikleri vurgulamıştır.

Çalışma, fintech'in Demokratik Kongo Cumhuriyeti gibi gelişmekte olan finansal sistemlerde banka performansını iyileştirmek ve finansal katılımı artırmak için uygun bir strateji olduğu sonucuna varmaktadır.

Anahtar Kelimeler: Acente Bankacılığı, Mobil Para, Finansal Performans, Özkaynak Kârlılığı, Fintech, Demokratik Kongo Cumhuriyeti.

DEDICATION

This thesis is dedicated to my family, whose unwavering support and encouragement have been a constant source of strength throughout my academic journey.

To my father, Ezechiel Tshibasu, and my mother, Gisèle Ngalula, I am deeply grateful for your love, prayers, and the values you instilled in me. Your sacrifices and steadfast belief in my potential have laid the foundation for all that I have pursued.

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LIST OF SYMBOLS AND ABBREVIATIONS

α	Intercept term in regression equation
β	Coefficient estimate
ε	Error term
ABN	Agency Banking Network
AFI	Alliance for Financial Inclusion
AML	Anti-money laundering
Apps	Software applications
ATM	Automated Teller Machine
BCC	Banque Centrale du Congo (Central Bank of Congo)
BCDC	Banque Centrale du Congo (Central Bank of Congo)
BGFibank	Banque Gabonaise et Française Internationale
BOA	Bank of Africa
CD	Customer Deposits
CGAA	Consumer Goods and Agency Association
DRC	Democratic Republic of Congo
e-finance	Electronic finance
F-statistic	Fisher-Snedecor statistic
FAS	Financial Access Survey
FE	Fixed Effects
Fintech	Financial Technology
FRED	Federal Reserve Economic Data
GDP	Gross Domestic Product
GLS	Generalised Least Squares

GSMA	Global System for Mobile Communications Association
IMF	International Monetary Fund
JB	Jarque-Bera (Normality Test)
LNABN	Log of Agency Banking Network
LNCD	Log of Customer Deposits
LNTA	Log of Total Assets
MMA	Mobile Money Accounts
MMP	Mobile Money Penetration
MMS	Mobile Money Subscription
NBI	Net Banking Income
NI	Net Income
NIM	Net Interest Margin
OLS	Ordinary Least Squares
POS	Point of Sale
PP-Fisher	Phillips–Perron Fisher Test
p-value	Probability value
R ²	Coefficient of Determination
RE	Random Effects
ROA	Return on Assets
ROE	Return on Equity
SA	Société Anonyme (Public Limited Company)
TAM	Technology Acceptance Model
TMB	Trust Merchant Bank
UBA	United Bank for Africa
UTAUT	Unified Theory of Acceptance and Use of Technology

VIF

Variance Inflation Factor

Chapter 1

INTRODUCTION

1.1 General Background

Financial Technology innovations have brought about significant transformations in the global financial industry. Arner, Barberis, and Buckley (2015) refer to fintech as the utilisation of technology to provide financial services. The vast array of services it includes is digital loans, online banking, blockchain technology, and mobile payment operations. The banking sector has experienced substantial effects from fintech advancements. As a result of these technologies, banks have extended their reach, reduced their dependence on physical structures, and become more responsive to their customers (Gomber, Koch, & Siering, 2017). Mobile money and agency banking are among the leading Fintech models in Sub-Saharan Africa. They have played an essential role in enhancing access to financial services in underserved areas.

Mobile money is a financial service that allows users to transfer and manage funds through mobile devices often without a bank account. Managed primarily by telecom providers, it has enabled millions of people to achieve the initial stage of financial inclusion, especially in remote areas.

Similarly, agency banking has emerged as an effective model for enhancing financial inclusion. This method enables banks to deliver financial services through permitted agents like local shops or kiosks, which work on behalf of the bank to offer services

like cash deposit, withdrawal, and account enquiry. To extend the reach of banks, agency banking serves as a cost-effective solution. This is particularly the case in rural or low-income areas where opening a branch is difficult or not possible. The World Bank (2021) notes that agency banking is a vehicle of financial inclusion in underserved regions of Sub-Saharan Africa.

Both mobile money and agency banking have shown a positive relationship with bank performance. Studies have linked fintech adoption to increased customer deposits, better liquidity, lower cost of service delivery, and higher profitability (Vives, 2017; Ozili, 2018). Banks can use these tools to diversify service channels, enhance customer base, and expand operations that lead to better performance and competitiveness.

The financial sector of the DRC is still largely underdeveloped compared to other regional leaders like Kenya, Nigeria, Ghana, Senegal, and others. The report of the study of the Congolese banking industry by Deloitte shows that the DRC's banking rate is only 8% in 2023 (Deloitte, 2024). The reach of traditional banking services is still constrained due to high dependency on cash, shortage of proper infrastructure, and low digital literacy. Nonetheless, the country is gradually embracing fintech to solve its financial inclusion problems. Mobile money platforms such as M-Pesa, Airtel Money, and Orange Money have expanded their reach in both urban and rural areas, offering basic financial solutions to populations formerly excluded from the formal banking services. Banks in the DRC have also tailored their business approaches to align with this fintech-driven evolution. Certain banks have created their own mobile money platforms, leading to greater integration of digital finance into their products and services. Some have formed strategic alliances with telecom-led mobile money providers, enabling wider reach to customers through interoperability and sharing of

infrastructure. At the same time, banks have invested in the agency banking network to complement their physical presence and lower costs.

1.2 Objectives

Although these innovations are promising, existing research on the impact of fintech on DRC bank performance is significantly limited. This study aims to fill this gap by analysing the Impact of fintech, particularly mobile money and agency banking, on the key variables of bank performance in DRC over the period 2018-2023. In pursuit of this objective, the study will be guided by questions such as: What is the impact of mobile money on the financial performance of banks in the DRC? What impact has agency banking had on the financial performance of banks in the DRC?

In an attempt to answer these questions, the study also seeks to determine whether the uptake of financial technology yields a statistically significant and positive effect on the performance of banks. The findings are expected to provide useful information to regulators, policymakers, and financial institutions who are interested in using fintech to foster economic growth, operational efficiency, and financial inclusion in the DRC.

1.3 Structure

The subsequent sections of the paper are structured as follow: Chapter 2 will review the literature on fintech adoption in the banking sector. Chapter 3 will cover the methods of data collection and analysis. Chapter 4 examines the study's results and their relevance to the banking sector in the DRC. Recommendations and future research are suggested in Chapter 5.

Chapter 2

LITERATURE REVIEW

This chapter surveys the current literature regarding the impact of fintech on bank performance. The following sections focus on two key fintech innovations that are relevant to the Democratic Republic of Congo (DRC). The aim is to discover how these technologies have affected the performance of banks at both international and local levels. The chapter provides a brief history of fintech, relevant theories, empirical evidence, common variables used, and a conceptual framework. It concludes by pointing out the research gap this study intends to address.

2.1 The History and Evolution of Financial Technology

Fintech refers to the combination of digital technologies with financial services to enhance the efficiency, accessibility, and affordability of these services. Fintech is not a recent phenomenon. The evolution of Fintech started in the mid-20th century with the introduction of credit cards in the 1950s, automated teller machines (ATMs) in the 1960s, electronic stock trading in the 1970s, and online banking in the 1990s (Arner et al., 2015).

But, after the 2008 Global Financial Crisis, the word ‘fintech’ became very popular. This refers to a new wave of technology-driven financial innovations, which were made possible due to increased scrutiny from regulators, loss of public trust, and the availability of smartphones and the Internet. Alternative financing options for businesses have been diversifying in the context of e-finance. These include mobile

applications for banking transactions, decentralized lending solutions, electronic wallets, automated financial advisors, and blockchain-based technologies (Gomber et al., 2017).

2.2 Theoretical Framework

Five theories were used in the study to explain the adoption of financial technology in the banking sector. These are the Diffusion of Innovation Theory, the Technology Acceptance Model (TAM), the Financial Intermediation Theory, the Transaction Cost Theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT). The aforementioned theories have a collective behavioural, operational, and strategic lens which show how the adoption of fintech through mobile money and agent-based banking impacts the profitability of banks in the DRC.

2.2.1 Diffusion of Innovation Theory

The theory by Rogers (1962) explains the diffusion of innovations throughout a social system over time. Adoption is based on the perceived attributes of innovations, such as relative advantage, compatibility, and complexity. This theory relates to the case of banking, whereby institutions adopt services more readily like agency banking or mobile money, depending on how aligned they are with the institutions' strategy, infrastructure, and market demand.

Banks in the DRC that perceive a strategic advantage in scaling access via agents or mobile platforms are more likely to adopt these technologies proactively.

2.2.2 Technology Acceptance Model (TAM)

According to Davis (1989), the Technology Acceptance Model (TAM) explains how the users —either individual consumers or institutions— accept new technology with regard to its perceived usefulness and ease of use. Fintech tools must be accessible, simple, and useful to Congolese banks and their clients for effective financial transactions in day-to-day life. TAM is particularly useful in understanding the success or failure of mobile banking based on usability and customers' views.

2.2.3 Financial Intermediation Theory

The theory, first proposed by Gurley and Shaw (1960), and later developed further by Diamond and Dybvig (1983), explains how banks serve as intermediaries for borrowers and lenders. Innovations in fintech such as mobile money and agency banking perform this function of intermediation by enabling financial institutions to serve previously excluded segments. In the case of DRC, these innovations improve the ability of banks to extend this intermediation role while potentially improving profitability by reducing costs and expanding their customer base.

2.2.4 Transaction Cost Theory

Transaction Cost theory was introduced by Coase (1937) and developed further by Williamson (1981). It suggested that organisations adopt a new method to reduce the cost of economic transactions. In the banking industry, agency banking and mobile money lower transaction costs by reducing the need for banks, staff, and paperwork. Customers incur lower costs through these channels thus making financial services more attractive. According to this theory, fintech should not be viewed solely as a front-end customer-facing tool, but rather as a cost-efficient mechanism that directly impacts the performance of banks.

2.2.5 Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT model, proposed by Venkatesh, Morris, Davis, and Davis (2003), extends the TAM by including additional variables like social influence, facilitating conditions, and user intention. This framework is especially useful for analysing technology adoption in low-income or fragile economies, where peer recommendations, network coverage, and institutional support strongly shape user adoption. The success of fintech depends not just on technology in DRC but also on trust within the community, existing mobile infrastructure, and regulatory support – factors that are well reflected in the UTAUT model.

Together, these theories suggest that the adoption of fintech —specifically mobile money and agency banking—can affect the operational and financial performance of banks in the DRC. They provide an understanding of factors driving adoption and emphasise the impact on the efficiency, outreach, and profitability of banks.

2.3 Existing Research on Fintech and the Banking Industry

2.3.1 Global Evidence on Fintech and Banking

Internationally, empirical evidence indicates that fintech adoption has transformed the banking sector through improved efficiency, enhanced customer experience, and lower operational costs. Numerous studies indicate that banks have reacted positively to fintech advancement by innovating service delivery, collaborating with fintech firms, and investing in digital services.

Navaretti, Calzolari, and Pozzolo (2017) explored whether fintech start-ups disrupt or complement banks. The study showed that banks that innovated early were able to enhance customer service, cut costs, and remain competitive. Similarly, Vives (2017)

argued that digital transformation is not only beneficial but also essential for European banks seeking to remain viable in a changing financial environment.

In a study of commercial banks in China, Chen, You, and Chang (2021) found that the adoption of digital technologies such as mobile payments and smart lending platforms was associated with improvements in the cost-to-income ratio, customer retention, and asset quality. Nevertheless, they observed that outcomes differed due to internal capacity, technology infrastructure, and regulatory environment.

The global evidence provides positive results, however, some authors have cautioned that the benefits of adopting fintech are not automatic. The successful integration depends on several factors such as institutional capacity, regulatory support, and user trust—particularly in more traditional or risk-averse banking systems.

2.3.2 Fintech and Bank Profitability

Research has recently emerged related to the impact of fintech on bank profitability. Across various contexts, studies have evaluated whether innovations like online banking, blockchain, digital payment, and agency banking influence performance indicators like return on equity (ROE), return on assets (ROA), net banking income (NBI), and net interest margin (NIM). These studies mostly use panel data regressions, fixed-effects models or random-effects and Granger causality techniques to test the strength and direction of fintech contribution to performance.

Gomber et al. (2017), through their cross-country study, mentioned that the integration of fintech services like automated lending platforms and blockchain-based settlement systems improves the operational performance of the market by increasing scale and lowering marginal costs. According to their findings, banks that used fintech in a

strategic way have witnessed benefits in profitability. Vives (2017) also suggested that fintech allows for efficiency gains through process automation and digital channels, particularly where customer acquisition and service delivery costs can be considerably reduced. Ozili (2018) further argues that fintech is the enabler of the financial intermediary which increases access to finance as well as increases bank revenues.

2.3.3 Empirical Studies in Sub-Saharan Africa and the DRC

In Sub-Saharan Africa, fintech has played a key role in reshaping the banking industry, providing new avenues for financial inclusion and operational efficiency. Numerous country-level studies have surfaced over the past few years, emphasizing the area's increasing dependence on digital financial services to tackle persistent gaps in access and performance.

According to a study done by Ndambuki (2016) in Kenya, agency banking had a positive effect on the profitability of banks represented by ROE. Similarly, Kolawole et al. (2024) In Nigeria, ran Granger causality tests to show how fintech adoption caused improvements in ROA. Such improvements were due to faster and more efficient mobile transactions. These studies strengthen the general notion that fintech adoption in Africa can lead to performance improvements for commercial banks.

Compared to other nations, the DRC is under-represented in literature. Despite the rapid expansion of Fintech, in particular mobile money and agency banking in the Congolese market, few academic studies have assessed its effects on bank profitability. A report by Global System for Mobile Communications Association (GSMA, 2013) has noted that the uptake of mobile money in the DRC is growing with the ability to expand access to finance. Similarly, the Banque Centrale du Congo (BCC) periodically publishes reports on mobile transaction volumes and the growth of the agency banking.

However, these publications do not include econometric analysis or assess the impact on institutional performance.

Given the lack of academic research, various industry sources have made efforts to fill the gap. Deloitte (2022) reveals that the DRC is one of those countries with the lowest banking penetration rate in Africa and yet it retains significant potential for transformation through fintech adoption. According to Deloitte (2024), the banking landscape in the DRC has undergone a notable transformation through the adoption of agency banking and mobile money services. By 2022, the number of banking agents had expanded to 11,431, with major banks such as Equity BCDC, TMB, Access Bank, Ecobank, Rawbank, and FirstBank establishing extensive agent networks across the country. This shift from traditional physical branches to more accessible, agency banking has proven effective in addressing the infrastructural challenges and limited accessibility in many regions. Furthermore, mobile money has emerged as a key driver of financial inclusion, with a penetration rate that reached 39.4% by 2023. Deloitte emphasises the strategic importance of partnerships between banks and mobile money operators, presenting them as mutually beneficial alliances capable of significantly improving banking sector performance and extending financial reach. Thus, banks and mobile money operators may significantly improve the performance of the banking sector and enhance financial reach.

Beyond industry expansion, the effectiveness of fintech in the DRC is also shaped by the regulatory environment. The BCC has gradually introduced measures to regulate mobile payment services and agency banking, notably with the publication of Instruction No. 24 in 2011, which authorises banks to use third-party agents (BCC, 2011). More recently, the BCC updated its regulatory guidelines in 2020 to strengthen

consumer protection, reinforce anti-money laundering (AML) requirements and clarify responsibilities of banks and mobile money operators (BCC, 2020). International organisations also highlight the importance of these regulatory measures. The GSMA (2013) indicated that early adoption of mobile money in the DRC was hampered by weak infrastructure and regulatory uncertainty, while more recent studies by Deloitte (2024) highlight that clearer regulatory frameworks have been instrumental to establishing partnerships between banks and financial technology service providers. Similarly, the World Bank (2021) emphasises that regulatory clarity is essential for improving financial inclusion in fragile economies such as the DRC. These regulatory reforms are therefore a key component of the financial technology ecosystem, as they determine the impact of innovations such as agency banking and mobile money on bank performance.

2.4 Variables and Proxies Used in Previous Studies

Most studies that assess how fintech affects bank performance typically draw their conclusions from a structured framework comprising dependent, independent as well as control variables. The choice of variables is typically made as per the availability of data and research objective and also the banking economic environment. This section describes the most common proxies that have been used in the literature for bank profitability, fintech adoption, and contextual factors affecting bank outcomes.

2.4.1 Dependent Variables: Proxies for Bank Profitability and Performance

In fintech–banking research, dependent variables are mainly intended to measure the financial or operational performance of banks. Return on Assets (ROA) and Return on Equity (ROE) are among the most common indicators. ROA assesses a bank's ability to generate profits from its total assets. It is considered a good measure of operational efficiency and managerial effectiveness (Athanasoglou, Brissimis, & Delis, 2008).

ROE reflects the returns provided to shareholders and is widely recognised as a fundamental indicator of financial performance (Athanasoglou et al., 2008).

2.4.2 Independent Variables: Fintech Adoption Proxies

Independent variables are employed to measure the level and nature of fintech adoption within the banking sector. These variables often represent the digital transformation extent in financial services. One of the most relevant indicators in low-income and underbanked regions is Mobile Money Penetration, typically measured through the number of accounts per 1,000 adults or transaction volume and value. This proxy is especially pertinent where fintech is predominantly accessed via mobile platforms (GSMA, 2024). Another vital measure is the Agency Banking Network, which refers to the number of agents operating under the bank's oversight who facilitate remote banking transactions using digital tools such as mobile apps or POS devices. This proxy reflects both the reach and cost-efficiency of fintech services (Consumer Goods and Agency Association [CGAA], 2023).

In addition, Digital Transaction Volume which relates to the frequency or value of mobile and Internet banking transactions is used to assess the levels of digital engagement (Arner et al., 2015). Researchers in cross-country contexts use broader measures such as a Fintech Development Index to assess countries' digital finance infrastructure and innovation capacity (World Bank, 2021; Alliance for Financial Inclusion [AFI], 2020). These proxies derive their value from the structural characteristics of the financial sector. In the case of the DRC, mobile money and agency banking remain the most plausible and readily available indicators of fintech adoption.

2.4.3 Control Variables

To ensure that empirical estimations of fintech's impact are not biased by omitted factors, control variables are used. These variables, which are known to influence banking performance, could be bank-specific (micro-level) or could be macroeconomic.

Total Assets are often used as a proxy for bank size and resource capacity and reflects the potential for economies of scale (Sufian & Chong, 2008). Customer loans serve to capture the extent of credit issuance, which is associated with income generation and risk exposure (Sufian & Chong, 2008; Dietrich & Wanzenried, 2011). Similarly, Customer Deposits reflect customer trust and the stability of a bank's funding base (Haddawee & Flayyih, 2020; Dilrangi et al., 2018). Lastly, the Capital Adequacy Ratio or the equity-to-asset ratio indicates a bank's financial resilience and ability to absorb losses (Nguyen, 2020; Ajayi, Ajayi, Enimola, & Orugun, 2019).

Gross Domestic Product (GDP) growth is included to represent the state of the economy and its influence on the banking sector's operational environment and credit demand (Sufian & Chong, 2008; Dietrich & Wanzenried, 2011). The Inflation Rate is a standard macroeconomic control variable, as it affects the real returns on financial products, pricing of loans, and operational costs. This inclusion is empirically supported in banking studies that consider inflation as a determinant of profitability (Sufian & Chong, 2008).

The control variables thus help to ensure the regression models are robust enough to isolate the effect of the adoption of fintech on bank performance from other economic and institutional factors.

2.5 Conceptual Framework

This study examines the relationship between financial technology and bank performance in the DRC, focusing on two fintech delivery models: mobile money and agency banking. Guided by theoretical and empirical literature, the conceptual framework assumes that these innovations improve profitability by reducing operational costs, expanding customer reach, and increasing transaction volumes.

Mobile money is understood as a technology-enabled service that facilitates basic financial transactions via mobile phones, especially in areas where formal banking network is limited. Its rapid expansion in the DRC—mainly through mobile network operators—has contributed to greater financial access and activity (GSMA, 2013). Similarly, agency banking extends banking services through authorised third-party agents, enhancing outreach and cost-efficiency (Ndambuki, 2016).

Bank performance in this study is captured through Return on Equity (ROE), a standard metric reflecting shareholder value and operational efficiency. In addition to the two fintech variables, the framework incorporates control variables—Total assets and Customer Deposits—to account for traditional intermediation functions, which have also been shown to influence profitability (Sufian & Chong, 2008; Haddawee & Flayyih, 2020; Dilrangi et al., 2018).

The conceptual framework therefore posits that fintech innovations—captured through mobile money (at the sector level) and agency banking (at the institutional level)—are positively associated with bank performance, measured by ROE. The model representing the expected relationships based on the final empirical specification of the study is presented in Figure 1.

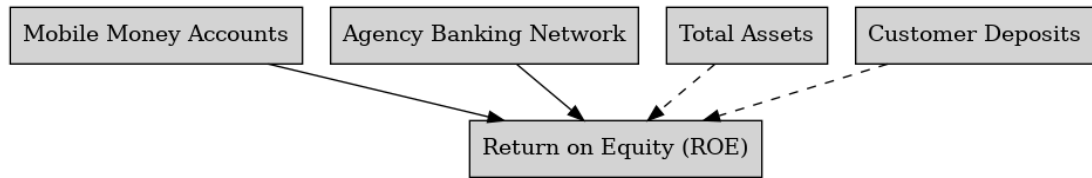


Figure 1: Conceptual Model Linking Fintech Adoption to Bank Performance

2.6 Research Gap and Justification for the Study

The academic discussion surrounding the effect of fintech solutions on the banking industry has been extensive. Yet, most empirical studies have focused on the relatively advanced African economies of Kenya, Nigeria, and Ghana. On the other hand, data-driven research assessing the influence of fintech on the profitability of banks in fragile and less developed financial systems, such as those in the DRC, is still lacking.

The existing literature on the DRC is quite limited and tends to focus primarily on financial inclusion and access rather than examining how fintech affects profitability and institutional outcomes for banks. While mobile money and agency banking seem promising in enhancing outreach and efficiencies, their contribution to the performance of banks, especially in the Congolese context, is less explored and empirically less verified.

Furthermore, many previous studies fail to distinguish between different models of fintech delivery. Although agency banking is generally managed and controlled by banks, mobile money has a more general sectoral perspective and can include various players. Without such a distinction, our insight is limited regarding the institutional ramifications of fintech adoption.

Another critical shortcoming in the literature is methodological. Many studies utilise cross-sectional designs or descriptive data. Therefore, these are inadequate for capturing longitudinal trends. In addition, most of the available evidence predates the COVID-19 wave of digital acceleration and does not reflect the changing fintech environment in the DRC.

The DRC presents a unique context for fintech research due to its combination of low banking penetration, large rural population, infrastructure challenges, and evolving regulatory environment. According to Deloitte (2024), the banking rate is 8% , while mobile phone penetration is rapidly growing, creating a fertile ground for digital financial services. The country faces logistical difficulties such as poor road networks, inconsistent electricity supply, and limited branch networks, which restrict physical access to banking. Moreover, the Congolese economy is highly cash-dependent, and informal financial practices are widespread, which further limits the ability of traditional banking models to reach underserved populations. At the same time, the regulatory framework is still developing, with the BCC gradually introducing measures for the regulation of mobile payments, agency banking, and consumer protection (BCC, 2011; 2020). This combination of infrastructural, institutional, and regulatory characteristics positions the DRC as an ideal case study to examine the role of fintech in improving bank performance under challenging conditions.

This research seeks to fill these gaps by examining the effect of two fintech delivery mechanisms—mobile money and agency banking—on the financial performance of commercial banks in the DRC. By drawing on both national and bank-level fintech data and bank-level performance indicators, the study captures a broader and more nuanced picture than previous case-specific or cross-sectional studies. This study

contributes to the literature by considering the under-researched Congolese banking sector where fintech activity is developing, yet its institutional impact remains unexamined. It assesses two types of fintech to determine their impacts on banks' performance as measured by panel data across banks over time. Additionally, the study links fintech adoption with profitability while accounting for core banking functions, offering a more comprehensive understanding of fintech's role in shaping bank outcomes in the DRC.

Chapter 3

METHODOLOGY

The present chapter describes the research approach used to examine the impact of financial technology on the performance and profitability of commercial banks in the DRC. Particular emphasis is placed on agency banking network and mobile money systems. Research methods are based on the nature of the research questions, the structure of the data set, and the need for statistical validation. The study uses panel data econometrics with diagnostic tests to generate reliable results on the impact of fintech adoption on the Congolese banking sector.

3.1 Research Design

The research design of this study uses quantitative and explanatory panel data analysis. Given the goal of assessing the effect of the fintech uptake on the performance of banks over time, this approach is appropriate for both cross-sectional (across banks) and time-series (2018–2023) analyses. According to Saunders, Lewis, and Thornhill (2023), the quantitative component of the research facilitates objectivity and accuracy in the assessment of financial performance, while the explanatory aspect allows the researcher to evaluate directional relationships between variables rather than simply describing them.

The panel data method is advantageous in the field of banking studies; it permits the control of unobserved heterogeneity. In addition, it increases the efficiency of econometric estimators (Hsiao, 2014). It also enables the identification of time-specific

and entity-specific effects, which are especially useful for technology impact evaluations across financial institutions.

3.2 Data Source and Description

This study draws on a panel dataset comprising twelve commercial banks operating in the DRC from 2018 to 2023. According to the Central Bank of Congo, there were 15 licensed commercial banks in 2024. Out of these, the 12 banks included in the dataset were selected based on data availability and together represented approximately 81% of the market share based on total assets in 2023. This coverage ensures that the analysis reflects the majority of the Congolese banking sector's performance and the uptake of financial technologies.

The dataset combines bank-level financial indicators with a sector-level fintech indicator. It provides a balanced framework to analyse the link between technological adoption and bank performance within the Congolese financial sector. The bank-level data were compiled from the Deloitte Congo banking sector reports, which aggregate publicly available financial figures published by individual banks in their annual reports. The primary fintech indicator, the number of agency banking Network (ABN), was sourced from the Ministry of Finance's official publication, the *Stratégie Nationale d'Inclusion Financière*. This document gives the national consolidated data on the growth of agent banking infrastructure for the banking industry as part of the greater financial inclusion goal of DRC.

Further, national-level data on mobile money accounts (MMA) has been obtained from the International Monetary Fund's Financial Access Survey (FAS), published through the Federal Reserve Bank of St. Louis (FRED) database. The dataset created features

both cross-sectional and time-series dimensions allowing a strong panel data analysis on fintech and bank performance in DRC. Table 1 presents the overview of the banks used in this study.

Table 1: List of Banks Included in the Panel Data Sample (2018-2023)

Bank name
1. Access Bank RDC
2. BGFibank
3. Bank of Africa RDC SA (BOA)
4. Citi Group Congo SA
5. Ecobank
6. Equity Banque Commerciale du Congo SA (Equity BCDC)
7. FirstBank RDC SA
8. Rawbank
9. Sofibanque SA
10. Standard Bank Congo
11. Trust Merchant Bank (TMB)
12. United Bank for Africa RDC SA (UBA)

3.3 Variables

This study uses a set of variables designed to assess the impact of financial technology on the performance of commercial banks in the DRC between 2018 and 2023. The dependent variable chosen is the return on equity (ROE), a widely accepted measure of bank profitability. ROE captures the return generated on equity and reflects the efficiency with which a bank transforms its capital into net profits. Higher values indicate better performance and better utilisation of capital resources. This metric is frequently employed in banking studies examining profitability drivers (Abbasoğlu, Aysan, & Güneş, 2007; Kosmidou, 2008).

To represent the fintech dimension, two independent variables are included. The first is the agency banking network (LNABN), which serves as a proxy for the adoption of

digital financial delivery channels. This variable captures the scale of agency banking activity across the sector. Since agent-level data for individual banks were not available, aggregated bank-level figures were proportionally allocated based on each bank's share of total assets, in line with approaches used in prior research where micro-level data were limited (Beck & Demirgüç-Kunt, 2006).

The second fintech-related variable is mobile money accounts (D_LOG_MMA), which reflects the annual growth in the use of mobile money in the country. As banks move into an increasingly digital financial environment, the expansion of mobile money services—although largely driven by telecommunications operators—has indirect implications on banking performance through competition, partnerships, and changes in customer behaviour. Due to the unavailability of data beyond 2020, figures for 2021-2023 have been estimated using forecasting techniques based on historical trends (2013-2020) in EViews, consistent with practices adopted in empirical studies of fintechs (Donou-Adonsou & Sylwester, 2016).

In addition to fintech indicators, two control variables were introduced to take into account bank-specific characteristics. Total assets (LNTA) is used to capture the size of the bank, which can influence profitability through economies of scale or scope. However, the relationship can also be negative if large banks suffer from inefficiencies due to bureaucratic structures or increased operational complexity (Athanasoglou et al., 2008). Finally, customer deposits (LNCD) are included to reflect the funding base and public confidence in the banks. Higher volumes of deposits often provide stable, low-cost funding, which can have a positive impact on profitability if managed effectively. Table 2 presents the variables used to assess bank profitability and its main

determinants, together with their notations and expected signs based on existing literature.

Table 2: Descriptive of the Variables Used in the Regression Models

Variable	Description	Hypothesized relationship with profitability
Dependent		
ROE	Return on Equity: net income divided by shareholders' equity. Reflects profitability.	NA
Independent		
LNABN	Natural log of the estimated number of agency banking agents. Proxy for fintech adoption.	+
D_LOG_MMA	First-differenced log of mobile money accounts. Measures digital financial inclusion growth.	+
Controls		
LNTA	Natural log of total assets. Proxy for bank size.	+ / –
LNCD	Natural log of customer deposits. Reflects funding stability and bank confidence.	+

3.4 Model Specification

The relationship between fintech adoption and bank performance is modelled as follows:

$$ROE_{it} = \alpha + \beta_1 \ln(ABN_{it}) + \beta_2 \Delta \ln(MMA_t) + \beta_3 \ln(TA_{it}) + \beta_4 \ln(CD_{it}) + \varepsilon_{it}$$

Where ROE represents the banks' return on shareholders' equity in year t, serving as the dependent variable. The parameter α (alpha) represents the intercept, while β_1 to β_4 are the estimated coefficients capturing the effect of the explanatory variables. The variable $\ln(ABN_{it})$ denotes the natural logarithm of the number of bank agency banking network i in year t. $\Delta \ln(MMA_t)$ denotes the first difference of the log-transformed

number of mobile money accounts, applied uniformly to all banks to reflect national fintech trends. $\ln(TA_{it})$ and $\ln(CD_{it})$ denote the natural logarithms of total assets and customer deposits, respectively, for each bank and year. Finally, ε_{it} captures the error term.

3.5 Hypothesis

The model was developed to test the following hypotheses:

H₀: Fintech adoption has an impact on the financial profitability of commercial banks in the DRC.

H₁: Fintech adoption has no impact on the financial profitability of commercial banks in the DRC.

These hypotheses are evaluated through the significance and direction of the estimated coefficients in the panel regression model.

3.6 Estimation Techniques

To evaluate the effect of financial technology on the performance of banks a panel data regression framework was employed. This technique is especially appropriate when the data involves multiple entities observed over time since it controls for unobserved heterogeneity and improves estimator efficiency by exploiting both cross-sectional and time-series variation (Baltagi, 2008).

3.6.1 Data Transformation and Stationarity Testing

To ensure that the data was appropriate for regression analysis, all variables were tested for stationarity using standard unit tests, including the Levin-Lin-Chu (LLC) and Phillips-Perron Fisher (PP-Fisher) tests. Appropriate transformations have been applied. The variable of mobile money accounts was log-transformed and differentiated to obtain stationarity, while the agency's banking network, total assets,

and client deposits were log-transformed to reduce asymmetry and stabilize variance. Return on equity (ROE) was used in the levels because it met the requirements of stationarity. These adjustments ensured the validity of the regression analysis and the reliability of statistical inferences. A summary of the results of the stationary tests is presented in Chapter 4.

3.6.2 Panel Model Estimation and Selection

To estimate the relationship between fintech adoption and bank performance, three panel regression models have been employed namely Pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE). The pooled OLS model assumes uniformity across all banks and time periods. The fixed effects model accounts for unobserved, time-invariant characteristics specific to each bank. In contrast, the random effects model assumes that individual effects are random and uncorrelated with the regressors. The Hausman test was employed to determine the most appropriate model specification by comparing the fixed and random effects models. This test assesses whether the unobserved effects are correlated with the explanatory variables, which guides the final model selection.

3.6.3 Diagnostic Tests

Diagnostic tests were carried out to assess the reliability of the regression model. Multicollinearity was assessed using the correlation matrix to ensure that the explanatory variables were not excessively correlated. To assess the autocorrelation, which indicates the serial correlation of the residuals, the Durbin–Watson (DW) statistic, generated from the regression output was used, the white cross-section robust standard errors were applied to correct for potential heteroskedasticity and ensure the robustness of inference.

Data analysis was carried out using EViews 12, which facilitated unit root tests, model estimation, missing value prediction, and variable transformations such as logarithmic conversion and differencing. Microsoft Excel 2016 was used for data preparation, including cleaning, formatting, bank-year series alignment, and calculation of derived variables. The combined use of Excel and EViews ensured a systematic and reliable analytical process throughout the study.

Chapter 4

EMPIRICAL RESULTS AND INTERPRETATION

The empirical results of the study and the interpretation of the link between financial technology adoption and the financial performance of DRC's banks are presented in this chapter. The results are contextualised within the structural characteristics of the DRC's financial sector and are evaluated to ensure robustness and econometric validity.

4.1 Descriptive Statistics

Descriptive statistics are used to summarise and understand the basic features of the data before proceeding with regression analysis. This includes the central tendency, dispersion, and distribution shape of both bank-level and sector-level variables. Table 3 displays the descriptive statistics for key variables:

Table 3: Summary of Descriptive Statistics of Dependent and Explanatory Variables

	Obs	Mean	Min	Max	Std. Dev
ROE	72	0.08	-2.46	2.46	1.00
LNABN	60	5.72	3.74	8.16	0.98
D_LOG_MMA	60	0.07	-0.02	0.21	0.08
LNTA	60	20.22	18.32	22.29	1.01
LNCD	60	19.79	17.37	22.04	1.21

Descriptive statistics provide an overview of the characteristics of the data set. The return on equity (ROE) has a mean value of 0.08, indicating an average profitability for all banks. However, the extreme values -2.46 and 2.46 and the standard deviation

of 1.00 show considerable variation, with some banks performing poorly while others achieved high returns. The fintech indicators—LNABN and D_LOG_MMA—each includes 60 observations due to transformations. LNABN averages 5.72 and varies moderately, while D_LOG_MMA has a mean of 0.07 and standard deviation of 0.08, showing consistent growth in mobile money adoption. The control variables, LNTA and LNCD, also have 60 observations. Their mean values are 20.22 and 19.79 respectively, with moderate variation, suggesting differences in bank size and deposit levels. Overall, the data show sufficient variability to support a valid regression analysis.

4.2 Stationarity

To ensure the suitability of the dataset for regression analysis, each variable was tested for stationarity. The tests and transformation results are summarised in Table 4.

The stationarity test results indicate that ROE is stationary across all test specifications, including models with trend and intercept, drift and without a trend components. Thus, its use in regression does not require additional transformations. LNABN also exhibits stationary, especially under the specification which includes trend and interception, implying deterministic trend exist in the time series of LNABN. D_LOG_MM presents solid evidence of stationarity in the LLC test and some support in the PPF test, showing that the transformation was appropriate. Likewise, the two control variables – LNTA and LNCD are stationary mainly under models with drift or trend. Thus, they can be included in the model in levels. Overall, these results validate the treatment of study variables and support their use in panel regression models, minimizing the risk of misleading results according to established econometric practice (Baltagi, 2008; Wooldridge, 2010).

Table 4: Summary of Stationarity Test Results

Levels		LLC	PPF
ROE	τ_T	-9.74*	46.27*
	τ_μ	-5.69*	36.13***
	τ	-1.33***	34.14***
LNABN	τ_T	-10.72*	50.07*
	τ_μ	3.02	2.25
	τ	5.81	1.21
D_LOG_MMA	τ_T	-6.38*	6.37
	τ_μ	-6.88*	37.33**
	τ	-4.38*	39.47**
LNTA	τ_T	-5.15*	26.71
	τ_μ	-2.98*	35.99***
	τ	9.51	0.97
LNCD	τ_T	-5.04*	25.36
	τ_μ	-5.20*	48.39*
	τ	8.23	2.17

Note: τ_T denotes the most comprehensive model with a drift and trend; τ_μ refers to a model that includes only a constant, without a trend; τ is the most constrained model with neither a constant nor a trend. The optimal number of lags is determined using the Schwarz Criterion. The symbols *, ** and *** denotes rejection of the null hypothesis at the 1%, 5% and 10% levels respectively.

4.4 Model Estimation Results

The results of regression models that were estimated using pooled OLS, fixed effects, and random effects are presented in this section. Key model diagnostics (R^2 , adjusted R^2 , F-statistic, and the Durbin-Watson statistic) are summarised in Table 5 to assess model fit and guide the selection of the most appropriate specification for the panel data.

Table 5: Summary of Model Estimations

Estimation Method	R ²	Adj.R ²	F-Stat(Prob)	D.W
Pooled OLS	0.30	0.25	0.00*	1.50
Fixed Effects	0.52	0.36	0.00*	2.13
Random Effects	0.31	0.27	0.00*	1.50

Note: *denotes rejection of the null hypothesis at the 1%

4.4.1 Model Selection

To determine the most appropriate model for interpretation, two specification tests were carried out: the redundant fixed effects test and the Hausman test. Table 6 summarises the results of these model selection tests.

The redundant fixed effects test yielded a p-value of 0.07, which lies between the 5% and 10% significance levels. This indicates that fixed effects may be slightly better than the pooled OLS model, but the evidence, at conventional significance levels, is not strong enough to justify their inclusion in the study. Conversely, the Hausman test produced a p-value of 1.00, which is significant at all significance levels, suggesting that the random effects model can be used in the study because it is consistent and efficient under the null hypothesis. The random effects model was selected as the appropriate one, based on the results and the balanced structure of the panel data.

Table 6: Model Selection Tests

Test	Null Hypothesis	p-value	Decision	Selected Model
Redundant Fixed Effects Test	Fixed effects not required (Pooled OLS sufficient)	0.07	Fail to reject → Pooled OLS acceptable	—
Hausman Test	RE is consistent and efficient	1.00	Fail to reject → Random Effects preferred	✓ Random Effects Model

4.5 Interpretation of the Final Model

The final regression results from the selected model, using the white cross-section (period-cluster) method, are given in this section. The model output is summarised in Table 7.

The regression analysis provides evidence of significant relationships between the two fintech variables and bank profitability, measured by ROE thus rejecting the null hypothesis. LNABN is positively associated with the ROE, with a coefficient of 0.93 statistically significant at 10%. This means that a 1% increase in agency banking network results on average in an increase of 0.93 percentage points in ROE provided that the effect of, D_LOG_MMA, LnTA and LnCD are held constant. This study is in line with previous literature that supports that agency banking improves outreach and lowers operational costs, thus leading to better profitability (Babajide, Adegboye, & Omankhanlen, 2015; Ozili, 2018).

Table 7: Results of the Random Effects Regression

Var.	Coef.	Std. Error	t- Stat
LNABN	0.93***	0.37	2.52
D_LOG_MMA	3.74**	1.25	3.00
LNTA	-0.67***	0.31	-2.17
LNCD	0.13	0.19	0.69
Constant	5.41	2.15	2.51
R-squared	0.32		
Adj. R ²	0.28		
F-stat (p)	0.00*		
Obs.	60.00		

Note: *, **, and *** denote significance at 1%, 5%, and 10%, respectively.

Similarly, D_LOG_MMA has a positive and statistically significant coefficient of 3.74 at 5% significance level. This indicates that a 1% increase in mobile money account growth will cause on average an increase of 3.74 percentage points in ROE provided that the effect of the LnABN, LnTA, and LnCD are held constant. This supports the view that mobile money increases financial inclusion, enhances transaction volumes, and provides banks with new revenue sources (Demirgüç-Kunt et al., 2018; Mbiti & Weil, 2016).

On the other hand, LNTA, which indicates the size of the bank, has a negative sign and a significant relationship with ROE (coefficient = -0.67, $p < 0.01$). This implies that bigger banks seem to observe a fall in marginal returns or a rise in inefficiencies, an observation consistent with the “too big to be managed” hypothesis (Berger & Mester, 1997). LNCD, although positive (0.13), is not statistically significant, which implies that variations in deposit levels are not sufficient to explain significantly the differences in profitability over the sampling period used in this study.

The model gives an R^2 of 0.32 and an adjusted R^2 of 0.28, indicating that on average 28–32% of the variation in ROE is explained by the model. The overall model is statistically significant, with an F-statistic (p-value) of 0.00, confirming the joint relevance of the explanatory variables. These results highlight the increasing significance of financial technology adoption, in particular agency banking network and mobile money, as key drivers of banking performance in emerging markets like the DRC.

4.6 Diagnostic Tests

4.6.1 Multicollinearity

To ensure the reliability of regression estimates, a correlation matrix was run to assess the potential multicollinearity between independent variables. Table 8 shows the correlation coefficients between LNABN, D_LOG_MMA, LNTA, and LNCD.

Table 8: Covariance Matrix

Independent Variables	LNABN	D_LOG_MMA	LNTA	LNCD
LNABN	1.00			
D_LOG_MMA	0.13	1.00		
LNTA	0.92	0.16	1.00	
LNCD	0.86	0.17	0.94	1.00

As a general rule of thumb, correlation coefficients below 0.95 are considered acceptable and suggest the absence of perfect correlation among independent variables. Such levels are commonly viewed as indicating no serious multicollinearity concerns in empirical research.

As indicated above, all correlation coefficients fall below the 0.95. The variables are sufficiently different from one another, allowing their inclusion in the model. The

results give confidence on the validity of the model specification which suggests that the estimated coefficients are not negatively affected by multicollinearity.

4.6.2 Residual Diagnosis

Residual diagnostic tests were conducted to validate and ensure the robustness of the final random effects model. They include tests of normality, cross-sectional dependence, heteroscedasticity, and serial correlation. The results are presented in Table 9.

Table 9: Summary of Diagnostic Test Results

Test	Null Hypothesis	Test output	Prob.
Normality (JB)	Residuals are normally distributed	—	0.52*
Cross-Sectional Dependence (CD)	No cross-sectional dependence	T.test = 2.35	0.02*
Heteroscedasticity (White)	Homoscedasticity	—	—
Serial Correlation (DW stat)	No autocorrelation	DW = 1.62	—

Note: * denote significance at 1%.

The diagnostic tests confirm the overall robustness and validity of the econometric model applied to banking data in the DRC. The Jarque–Bera test returns a p-value of 0.52, indicating that the residuals are, on average, normally distributed and meet a key hypothesis of linear regression analysis (Gujarati & Porter, 2009). The Pesaran Cross-Sectional dependence (CD) test produced a test statistic of 2.35 with a p-value of 0.02. Although this suggests some degree of cross-sectional dependence at 5% significance level, it remains statistically significant at 1% significance level. To correct any residual cross-sectional Dependence and heteroscedasticity, the white cross-section (period-cluster) method was applied to compute robust standard errors, improving the

reliability of statistical inference without affecting the coefficient estimates (Baltagi, 2008; Wooldridge, 2010).

The Durbin-Watson statistic of 1.62 is reasonably close to the benchmark value of 2.00 indicating autocorrelation is within an acceptable limit for short panel dataset. This is particularly acceptable when robust estimation techniques are used to address potential serial correlation problems (Drukker, 2003). Taken together, these diagnostic results confirm that the final specification of the model is well-suited to analyse the performance of banks working in the unique structural environment of the DRC banking sector.

Chapter 5

CONCLUSION AND RECOMMENDATIONS

This chapter summarises the study in line with the objectives and methodological approach discussed in the preceding chapters. The conclusions provided are based on the findings obtained and relate to the research questions on the influence of agency banking and mobile money on the financial profitability of commercial banks in the DRC. The chapter also presents the limitations of the study and gives recommendations. Finally, it identifies research areas that could be explored in light of the study's results.

5.1 Summary and Conclusion

This research used the econometric panel data approach to examine the effect of agency banking and mobile money on the performance of twelve commercial banks in DRC between 2018 and 2023. The main performance indicator was the return on equity (ROE) while total assets (LNTA) and customer deposits (LNCD) served as control variables. The analysis results showed that agency banking and mobile money had a positive and statistically significant effect on ROE, leading to the rejection of the null hypothesis.

The findings suggest that the use of agency banking and mobile money has a beneficial effect on the performance of banks in the DRC. These fintech advances offer different methods to deliver services which helps reduce costs and reach more customers. Agency banking and mobile money services have revolutionised the banking and financial services industry, especially in rural areas, especially in rural areas, which

are often difficult for banks to reach. On the other hand fintech adoption not only strengthens the operational efficiency of banks but also enhances financial inclusion by enabling access to banking services in underserved rural and peri-urban areas. The study highlights that banks with larger agent networks and more extensive mobile money integration tend to perform better financially, reflecting the critical role of fintech in bridging infrastructural and accessibility gaps in the Congolese banking sector. The results also demonstrate that fintech solutions can accelerate the formalisation of savings and payments, reduce the reliance on cash transactions, and contribute to a more resilient financial system that is better able to withstand external shocks such as political instability or public health crises.

The study's findings imply that fintech emerges not merely as a convenience but as a critical driver of profitability and resilience for banks in the DRC. By extending banking services beyond traditional branches, banks can diversify their customer base, increase deposits, and ultimately improve their return on equity. Furthermore, the results indicate that fintech can serve as a strategic tool for national financial inclusion policies, allowing regulators and policymakers to promote economic growth through accessible digital financial solutions.

5.2 Recommendations

In light of the study's outcomes, the first set of recommendations is directed towards regulators. The Congolese authorities should strengthen the regulatory framework to clearly define the roles and responsibilities of banks and fintech providers, while also addressing interoperability and consumer protection. Developing national interoperability standards will enable smoother transactions across banks and mobile money operators, thereby reducing fragmentation in the financial system. Regulators

should also establish a central monitoring system for fintech usage and performance metrics, which will help detect operational and security risks early; public awareness campaigns are needed to build trust in digital finance, especially among populations that remain sceptical of electronic money.

For banks, the findings suggest that greater investment in agency banking infrastructure is needed to expand financial services to underserved areas. Banks should thoroughly train agents, equip them with secure devices, and ensure service reliability even in remote locations. Stronger collaboration between banks and mobile money operators should also be pursued, with secure data-sharing arrangements and co-designed financial products that address the needs of both urban and rural clients. Moreover, banks must prioritise cybersecurity by investing in encryption, multi-factor authentication, and fraud detection tools to safeguard client data and transactions.

However, despite these opportunities, several persistent challenges remain. Infrastructure weaknesses, including poor internet penetration, frequent electricity shortages, and uneven network coverage, hinder the efficiency and reliability of agency banking and mobile money services. Operational risks such as agent misconduct, weak oversight, and transaction delays may undermine customer confidence if not properly addressed. Cybersecurity threats represent an even greater concern, as the rapid digitisation of financial services has not always been matched by adequate investment in IT security systems.

The practical implications of these findings are clear: without significant improvements in digital infrastructure, governance, and security frameworks, the potential of fintech to transform banking in the DRC will remain limited. Banks and regulators should therefore adopt a proactive stance, investing not only in technology

but also in human capacity building through digital literacy programmes and ongoing agent training. At the policy level, a coordinated national strategy is needed to align the efforts of banks, fintechs, telecom providers, and regulators in order to create not only a secure, but also an inclusive and resilient digital finance ecosystem.

5.3 Limitations

Despite its contributions, the study was subject to several limitations. Mobile money Data were available only at the aggregate level preventing the possibility of institutional-level analysis. Moreover, a lack of bank-specific fintech indicators on agency banking necessitated a reliance on estimated proxies based on banks' market share. Finally, Due to the study's short time frame, long-term patterns and impacts were not observed in the research.

5.4 Areas for Further Research

Future studies should consider approaches such as interviews or case studies that can capture institutions' various viewpoints about fintech to further develop this study. In addition, access to disaggregated data on agency activity and mobile money transactions would allow for more granular analysis. Researchers may also wish to assess the impact of fintech on financial inclusion and customer satisfaction. Finally, comparative studies involving other Sub-Saharan African countries with similar economic contexts would help validate the findings and inform region-wide policy development.

In summary, this research reaffirms the strategic importance that agency banking and mobile money can have in reinforcing the performance of banks in support of inclusion in the DRC.

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USE OF ARTIFICIAL INTELLIGENCE

In this study, ChatGPT was employed as a support tool to enhance the writing process. It assisted with sentence structuring, drafting preliminary sections of the literature review, and generating illustrative graphics and tables aligned with the formatting requirements of the thesis.