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Financial Technology and Financial Inclusion in Emerging and Developing Economies

By

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A thesis submitted to the Graduate School of Business Administration of the University of the Witwatersrand in fulfilment of the requirements for the degree of Doctor of Philosophy.

October 2025

DECLARATION

I, Motlanalo Kgodisho Mashoene, declare that the research work reported in this dissertation is my own, except where otherwise indicated and acknowledged. It is submitted in fulfilment of the requirements for the degree of Doctor of Philosophy at the University of the Witwatersrand, Johannesburg. This thesis has not, either in whole or in part, been submitted for a degree or diploma to any other university.

Signed: _____

Date: _____

Motlanalo Mashoene

Johannesburg, South Africa

DEDICATION

This thesis is dedicated to my late mother, Irene Ramatsimele Pakgadi; my father, Bethuel Mathukhu Pakgadi; my incredible husband – Kopano Mashoene; my beautiful children – Lesego, Leago and Leano, my siblings (Pelebese, Khomotso, Lebogang, and Kamogelo) nephew (KaMohau), sister-in-law (Masello Mashoene) and niece (Tshiamo Mashoene).

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- My father, siblings, and sister-in-law for always being there with words of motivation and understanding, helping me stay focused and inspired.

- To my mother in heaven, this is for you!

- Lastly, I want to take a moment to express my deep gratitude to God for being with me throughout my PhD journey.

LIST OF PUBLICATIONS AND RESEARCH OUTPUTS

Peer Reviewed Publications

1. FinTech and Financial Inclusion in Emerging and Developing Economies: A System GMM Model. Cogent Social Sciences. (Manuscript accepted and published)
   Motlanalo Mashoene, George Tweneboah & Eric Schaling (2025) FinTech and financial inclusion in emerging and developing economies: a system GMM model, Cogent Social Sciences, 11:1, 2491701, DOI: 10.1080/23311886.2025.2491701

Papers in the process of Submission for Review

2. The effect of institutional quality on digital financial inclusion in emerging and developing economies. An ARDL approach. (Manuscript submitted)

3. The effect of digital financial inclusion on inclusive growth and poverty in emerging and developing economies. A System GMM Approach. (Manuscript submitted)

Conference Presentations

1. Wits Global Fintech Conference 2025
   Theme: "Global Fintech Trends"

ABSTRACT

Financial inclusion has been promoted as a worthy goal for all societies, and the global sustainable goals, among other national efforts, are geared towards access to basic financial services. Although financial inclusion has been the focus of numerous studies, there is still limited research on the role of financial technology (FinTech) in rural and urban areas, genders, and developed and emerging market dichotomy in access to financial services. Moreover, little is known about the effect of digital financial mechanisms on institutional quality, inclusive growth, and developed reduction. Recent advances in digitisation, artificial intelligence, and related technologies provide avenues for in-depth assessment of inclusive finance via the interface of FinTech in emerging and developing economies.

Covering 28 countries, this thesis investigated three primary themes, each aimed at addressing the existing knowledge gap. The first empirical study examined the role of financial technology (FinTech) in promoting financial inclusion across emerging and developing economies (EMDEs). While financial inclusion has been widely studied, limited research focuses on the concurrent impact of FinTech on financial access in multiple EMDEs. Using Principal Component Analysis (PCA), a new financial inclusion index was constructed, incorporating two dimensions: access and usage. A System Generalized Method of Moments (GMM) model was applied to examine the relationship between FinTech and financial inclusion, while the Ordinary Least Squares (OLS) technique was used to assess factors influencing barriers to inclusion. The results revealed that a 1% increase in FinTech leads to a 0.1772 unit rise in the financial inclusion index. Additionally, the study found that education, GNI per capita, and broad money to GDP affect barriers to financial inclusion.

The second empirical study analysed the effect of institutional quality on digital financial inclusion in EMDEs. Improving financial inclusion depends in part on the quality of institutions. However, there are limited studies on the relationship between institutional quality and financial inclusion from a digital perspective. The study empirically analysed the short and long-run cointegration between institutional quality and digital financial inclusion in EMDEs by using panel autoregressive distributed lag (ARDL) as the main estimation technique. Findings from the study revealed that institutional quality has a positive effect on digital financial inclusion in the long run but not in the short run.

The third empirical study investigated the effect of digital financial inclusion on inclusive growth and poverty in EMDEs. Providing underserved individuals and businesses with access

to financial services and products through technology and innovation empowers them, increases inclusive growth and alleviates poverty. Nonetheless, there is limited research on the effect of digital financial inclusion on poverty through the intervention of inclusive growth in the existing literature. The System-GMM results revealed that digital financial inclusion has a positive and significant effect on inclusive growth in EMDEs at a 10% significance level. The findings also highlight that inclusive growth has a negative and significant effect on poverty in EMDEs at a 5% significance level.

Keywords: digital financial inclusion, emerging and developing economies**,** financial inclusion, FinTech, inclusive growth, institutional quality, poverty

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LIST OF ABBREVIATIONS AND ACRONYMS

AFI	Alliance for Financial Inclusion
ARDL	Auto-Regressive Distributed Lag
ASU	Actual System Use
ASEAN	Association and Southeast Asian Nations
ATU	Attitude Towards Usage
CGAP	Consultative Group to Assist the Poor
CPI	Consumer Price Index
DFS	Digital Financial Services
DOI	Diffusion of Innovation Theory
EMDEs	Emerging and Developing Economies
FA	Factor Analysis
FGLS	Feasible Generalized Least Squares
FAS-IMF	Financial Access Survey of the IMF
FinTech	Financial Technology
FSB	Financial Stability Board
GDP	Gross Domestic Product
GNI	Gross National Income
GMM	Generalized Method of Moments
GPFI	Global Partnership for Financial Inclusion
IFC	International Finance Corporation
IFS	International Financial Statistics
IMF	International Monetary Fund
KMO	Kaiser–Meyer–Olkin
LAC	Latin America and the Caribbean
LSDV	Least Squares Dummy Variables
LIML	Limited Information Maximum Likelihood
MENA	Middle East and North Africa
MSMEs	Micro, Small and Medium Enterprises
NARDL	Nonlinear Autoregressive Distributed Lagged
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PU	Perceived Usefulness

PEOU	Perceived Ease of Use
PCA	Principal Component Analysis
SMEs	Small and Medium Enterprises
TAM	Technology Acceptance Model
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme
WAEMU	West African Economic and Monetary Union
WDI	World Development Indicators
WGI	Worldwide Governance Indicators

CHAPTER 1

INTRODUCTION

1.1 Background and Context of the Study

In recent years, various international agencies and initiatives have played a pivotal role in promoting financial inclusion through adopting financial technology (FinTech), particularly in Emerging and Developing Economies (EMDEs). Institutions such as the Alliance for Financial Inclusion (AFI), the Consultative Group to Assist the Poor (CGAP), and the Better Than Cash Alliance have led efforts to leverage FinTech innovations to extend financial services to underserved populations. The International Finance Corporation (IFC) has invested in FinTech startups in EMDEs, providing capital and expertise to scale solutions that enhance access to banking, credit, and insurance. Additionally, global bodies such as the Financial Stability Board (FSB) have established task forces to ensure that FinTech promotes financial inclusion while maintaining financial stability. These initiatives, alongside recent international reports such as the World Bank's Global Findex Report and the International Monetary Fund (IMF)'s assessment of FinTech in emerging markets, underscore the growing recognition of FinTech as a critical driver of inclusive financial systems in EMDEs.

Financial inclusion has emerged as a key focus for international organisations such as the Organisation for Economic Co-operation and Development (OECD), World Bank, AFI, and the IMF, given its critical role in poverty reduction and economic development. According to the World Bank's Global Findex Report (2021), over 1.4 billion people remain unbanked, with the majority residing in EMDEs. International bodies emphasise the potential of FinTech to bridge this gap by offering accessible, affordable, and innovative financial services. For instance, mobile money platforms such as M-Pesa in Kenya show how FinTech can drastically improve access to financial services in regions with limited traditional banking infrastructure. Recent reports, including the IMF's 2022 FinTech and Financial Inclusion Report, highlight the growing impact of digital financial services in promoting financial inclusion in EMDEs, urging governments to foster enabling environments for FinTech development.

1.1.1 The Rise of FinTech

FinTech adoption is increasing at different rates across regions and countries, with mobile money providers and other FinTech companies making significant advances into the financial industry. Global indices confirm this uneven growth, demonstrating that while the average consumer FinTech adoption rate has increased significantly worldwide, there are considerable regional differences, with some emerging markets consistently showing the highest adoption percentages (Ernst & Young, 2019). This is further evidenced by a strong correlation between FinTech activity and a country's mobile connectivity and financial infrastructure (World Bank, 2020). Several studies show a relationship between mobile money access and usage and growth in savings, borrowings, transfers, and remittances (Bharadwaj et al., 2019; Lyons et al., 2020). Similarly, Nguyen (2020) observes that mobile accounts have become a convenient method of executing financial transactions for many households in developing countries. FinTech can expedite financial services distribution to a significant proportion of the population (especially the unbanked). This can be accomplished by utilising cutting-edge technology at a reasonable cost and in a safe setting (Siddik et al., 2020).

In 2021, approximately 4.9 billion people used the internet. This implies that roughly 63% of the world's population was online (up 17%). However, 2.9 billion people in the world still do not have access to the internet, with 96% of them living in EMDEs. Furthermore, in 2021, the global penetration of mobile cellular subscriptions increased. Developing countries in Asia, the Pacific, and the Americas, drove the growth. In Africa, on the other hand, mobile cellular subscriptions decreased (International Telecommunication Union, 2021). Nonetheless, the banking and telecommunications sectors have taken advantage of the growing use of cell phones to pioneer the development and uptake of mobile-based FinTech services, particularly money transfers (Ehrbeck et al., 2012). This suggests that FinTech has the potential to improve financial inclusion in the regions due to the marked increase in internet and mobile penetration.

The McKinsey Global Institute published a report in September 2016 that quantified the expected economic impact of FinTech. According to the report, the cost of providing financial services can be lowered to 91% by mobile technology. Therefore, one of the main ways to speed up financial inclusion is expected to be through FinTech. Around 1.6 billion people in EMDEs could be provided access to financial services through digital financial services by 2025 (Manyika et al., 2016). Moreover, the GDP of emerging economies is forecasted to grow

by USD 3.7 trillion and generate about 95 million new jobs by 2025 because of digital financial services (Manyika et al., 2016).

1.1.2 Digital Finance

Digital finance (that is, FinTech-enabled finance) has attracted interest from scholars and policymakers as a means of alleviating poverty and increasing financial inclusion. All participants involved in the financial sector, including users of financial services, companies that supply digital financial services, regulators, decision-makers, and the economy benefit greatly from digital finance. A branchless technology-based banking system can lower service costs for banks and FinTech suppliers while increasing access to credit for the underprivileged and poor (Siddik et al., 2020).

Digital finance can increase access to financial services and enhance economic advancement in underdeveloped markets (Shen et al., 2021). According to the Consultative Group to Assist the Poor (2015), digital financial inclusion ensures access to essential financial services for underserved populations via technology-driven platforms. The World Bank (2014) defines digital financial inclusion as the deployment of cost-effective digital means to reach currently financially excluded and underserved populations with a range of formal financial services tailored to their needs that are responsibly delivered at a cost that is affordable to customers and sustainable for providers. A digital economy promotes economic growth and productivity (Dahlman et al., 2016). A study by Sy et al. (2019) points out that FinTech can improve and accelerate advances achieved in EMDEs in the past two decades. Khera et al. (2021) note that FinTech has also been shown to improve access to essential financial services, particularly in EMDEs.

1.1.3 Institutional Quality and Digital Finance

The intersection of institutional quality and digital finance has generated increasing attention in economic development, particularly in EMDEs. Institutional quality, encompassing dimensions such as control of corruption, rule of law, regulatory quality, government effectiveness, political stability and absence of violence/terrorism, and voice and accountability, serves as a critical determinant in shaping the landscape of financial services. In these contexts, robust institutions can adopt and expand digital financial services, increasing access to underserved populations. Conversely, weak institutional structures often lead to

barriers that inhibit the growth and effectiveness of digital financial services, exacerbating financial exclusion among marginalised groups.

a) *Regulatory Frameworks as a Measure of Institutional Quality*

One primary mechanism through which institutional quality influences digital financial inclusion is the establishment of effective regulatory frameworks. Regulatory bodies are essential in creating an environment conducive to innovation while ensuring consumer protection and stability. For instance, the success of mobile money services in Kenya can be attributed to the proactive regulatory stance adopted by the Central Bank of Kenya, which facilitated the rapid growth of platforms such as M-Pesa. Such regulatory foresight demonstrates how institutional quality can enhance the reach and utility of digital financial services.

b) *Public Trust as a Measure of Institutional Quality*

Moreover, public trust in institutions significantly impacts individuals' willingness to use digital financial solutions. In environments characterised by high levels of corruption and weak governance, potential users may exhibit scepticism towards digital financial services, fearing fraud or misuse of their data. Consequently, the legitimacy of institutions becomes paramount in building consumer confidence. Countries prioritising transparency, accountability, and anti-corruption measures enhance their institutional quality and create a favourable climate for digital financial inclusion. For example, countries such as Rwanda, which have invested in anti-corruption initiatives and governance reforms, have observed increased adoption of digital financial solutions as citizens gain trust in their systems.

c) *Infrastructure development as a Measure of Institutional Quality*

Infrastructure development, another critical facet of institutional quality, is essential for implementing digital financial services. Quality institutions are typically better equipped to allocate resources effectively towards enhancing technological infrastructure, such as internet connectivity and telecommunications networks. This infrastructure is vital for the operation of digital financial services, particularly in rural areas where traditional banking services are scarce. A comparative analysis of countries reveals that those with efficient institutional frameworks tend to invest more heavily in technological advancements, resulting in higher

levels of digital financial inclusion. For instance, India's Digital India initiative highlights how government-led efforts to improve digital infrastructure can lead to significant advancements in financial inclusion, particularly for rural populations.

1.1.4 The Role of Digital Financial Inclusion in Poverty Reduction Efforts

Poverty continues to be one of the most significant and enduring social challenges encountered by EMDEs. Global figures are concerning, with around 700 million individuals projected to be living in extreme poverty in 2024 (World Bank, 2024). This means that they earn less than $2.15 a day, a threshold that the World Bank classifies as the extreme poverty line. Combating poverty has been deemed an ethical, political, economic, and social responsibility for humanity owing to its detrimental effects on the well-being of people in general (World Bank, 2001; Ayoo, 2022). Digital financial inclusion has emerged as a tool for reducing poverty, particularly in EMDEs. In fact, in most EMDEs, the means for financial poverty alleviation has progressively shifted from traditional finance to a mix of traditional and digital financial inclusion (Yu & Wang, 2021).

One key factor impacting the state of the economy is access to financial products and services. For underserved populations, saving money, accessing credit, and making investments can alleviate poverty and achieve inclusive growth. Through digital financial services, underserved individuals and businesses can effectively participate in the system, thus eliminating barriers that have previously prevented them from participating. For instance, digital financial inclusion provides access to financial services and products through digital platforms such as electronic wallets and mobile banking (Kling et al., 2022), which are convenient and relatively easy for individuals and companies.

Economic growth alone is inadequate to achieve fair and equitable growth. Most developing countries prioritise inclusive growth to mitigate economic inequalities. The awareness that growth alone is not enough to eradicate poverty, and that ongoing inequality could negatively impact attempts to end poverty has prompted policymakers to search for alternative approaches (Lenka & Sharma, 2017). The inclusive growth approach is the latest strategy endorsed by policymakers to enhance living standards in EMDEs (Bakker, 2019). For instance, Asia adopted inclusive growth as the basis of its development strategy to foster economic opportunity and ensure that everyone has access to economic opportunities (Ali & Zhuang, 2007). In Africa, most countries adopted the "Maya Declaration," a global initiative for

financial inclusion that seeks to eradicate poverty and provide financial stability for all[1]. The eradication of poverty and increased financial inclusion in EMDEs are both made possible by inclusive growth strategies.

The economic growth in many developing countries is not evenly spread, as major cities and the construction sector capture a significant share of national wealth, often to the detriment of agricultural and rural development (Sarpong & Nketiah-Amponsah, 2022). Global dialogues have recognised that EMDEs need to pursue inclusive growth, as this expands beyond economic growth (Kouton, 2019). Inclusive growth is gaining significant momentum and aims to foster a comprehensive growth strategy that considers various factors, such as reducing income inequality, providing equitable and sustainable job opportunities for everyone, alleviating poverty, ensuring access to healthcare and clean water, offering educational opportunities, and raising overall living standards. Digital financial inclusion has the potential to alleviate poverty and achieve inclusive growth in EMDEs by increasing access to essential financial services and products, empowering underserved communities, and reducing banking costs.

1.2 Problem Statement

Existing literature illustrates that the relationship between FinTech and financial inclusion has primarily focused on specific countries or regions at a time. That is, there is limited focus on simultaneously examining this relationship in several EMDEs. For instance, in most African countries, FinTech has positively impacted financial inclusion (Kim, 2022; N'dri & Kakinaka, 2020; Tiony, 2023). According to the 2021 World Bank report, mobile money drives account ownership in Sub-Saharan. Despite notable advancements in this region, adults from historically disadvantaged backgrounds continue to face disparities regarding financial access (Demirgüç-Kunt et al., 2021). Empirical findings in the Middle East region are positive, showing that FinTech drives financial inclusion (Al-Smadi, 2023; Qamruzzaman, 2023). Despite empirical research suggesting that FinTech has a positive impact on financial inclusion in Asia (Erlianta et al., 2021; Qamruzzaman & Wei, 2019; Rosyadah et al., 2022), the persistence of the financial inclusion gap is underscored by data showing that a significant portion of the world's unbanked population remains concentrated in China and India

[1] The Maya Declaration is an international movement for responsible and sustainable financial inclusion that seeks to minimise poverty and provide economic stability for all.

(Demirgüç-Kunt et al., 2022). A detailed analysis of these regional disparities is provided in Chapter 2.

Existing literature also indicates that individuals who were previously unable to access financial services and products can now do so due to the impact of FinTech. However, there is still room for growth as some areas remain financially excluded. Although EMDEs face similar challenges in financial inclusion, their circumstances and needs might differ. Examining the EMDEs collectively rather than individually enables us to discover specific challenges unique to regions that FinTech could address across a variety of scenarios. Moreover, by analysing the EMDEs concurrently, information sharing is facilitated, thus enabling countries to leverage successful FinTech solutions from other countries to address their challenges.

This research addresses the financial inclusion challenge specifically how it can be enhanced in EMDEs. Financial inclusion entails the availability and accessibility of financial services such as savings, credit, insurance, and digital payments to all individuals, regardless of income or location. Despite global efforts, many EMDEs face barriers such as limited financial infrastructure, regulatory hurdles, and low financial literacy, which hinder widespread financial inclusion. This underscores the relationship between FinTech and financial inclusion, as FinTech can significantly lower these barriers by offering digital financial services that reach previously unbanked populations. It is important to clarify the scope of key terms used in this problem statement. This thesis examines financial inclusion through two lenses: the traditional dimension (for example, access to bank branches and ATMs) and the digital dimension (for example, access to and usage of mobile money and internet banking). While the first research question addresses the broader relationship between FinTech and financial inclusion, the second and third questions focus specifically on digital financial inclusion. The specific proxies and measures used for these constructs are detailed later in chapter two and chapter three.

A critical gap in the literature concerning FinTech services in EMDEs is the limited understanding of the factors influencing individual and business adoption behaviours. While existing research often focuses on the technical aspects of FinTech innovations, there is a lack of comprehensive studies focusing on cultural, socioeconomic, and infrastructural factors shaping FinTech adoption across diverse EMDEs. This gap is significant because, despite the potential of FinTech to drive financial inclusion, adoption rates remain uneven due to barriers such as digital literacy, trust in digital platforms, and access to reliable internet services. The

motivation behind addressing this gap lies in the pressing need to enhance financial inclusion and economic empowerment in EMDEs, where traditional financial systems have failed to meet the needs of underserved populations. The solution lies in identifying tailored strategies to increase FinTech usage, such as improving digital literacy programmes, enhancing user trust through stronger data security measures, and developing inclusive policies that promote equal access to digital financial services.

Dependable and efficient institutions create a conducive environment for digital financial services by ensuring financial stability and secure transactions. This, in turn, fosters interest in the formal financial sector among individuals and potential investors. Existing research indicates that the quality of institutions plays a significant role in enhancing financial inclusion (Kwenda & Chinoda, 2019). However, there is a notable gap in the literature regarding the relationship between institutional quality and financial inclusion from a digital perspective. Most studies have concentrated on traditional dimensions and indicators of financial inclusion, leaving a critical void in understanding how institutional quality influences digital financial inclusion. However, there is a notable gap in the literature regarding the relationship between institutional quality and financial inclusion from a digital perspective. As established in Section 1.1.3, the causal logic is clear, robust institutions create the necessary regulatory, trust, and infrastructure conditions that directly enable digital financial access and usage. Despite this, most existing studies have concentrated on traditional dimensions of financial inclusion, leaving a critical void in understanding how institutional quality influences digital financial inclusion specifically across a broad set of countries.

Moreover, the existing body of research has predominantly focused on individual countries rather than providing a comprehensive analysis across multiple EMDEs. This lack of cross-sectional studies limits our understanding of how institutional quality affects digital financial inclusion in diverse contexts, which is essential for formulating effective policies. Global discussion emphasises that EMDEs should strive for inclusive growth, surpassing the notion of economic growth (Kouton, 2019) as economic growth alone is not sufficient to achieve equitable growth. While previous studies have established that financial inclusion is a powerful tool in combating poverty, there remains a significant gap in the literature regarding the impact of digital financial inclusion on inclusive growth and poverty alleviation. Notably, there is a lack of empirical research examining how digital financial inclusion influences poverty through the lens of inclusive growth.

In summary, while the individual components of this pathway have been studied in isolation, a critical and overarching problem remains: the lack of a comprehensive, cross-country framework that connects FinTech adoption to its ultimate developmental goals in EMDEs. The literature is fragmented, with isolated studies on FinTech's potential, institutional enablers, or poverty outcomes, but fails to systematically trace how institutional quality governs the translation of FinTech into digital financial inclusion, and how that inclusion, in turn, drives inclusive growth and poverty reduction. This thesis addresses this synthesized problem by investigating this integrated pathway across a broad spectrum of emerging and developing economies. This research contributes valuable insights that can inform policy and practice, ultimately fostering a more inclusive financial landscape.

1.3 Research Questions

The research questions that follow arose because of the gaps identified in the existing literature:

1. What is the relationship between FinTech and financial inclusion in emerging and developing economies?
2. What is the effect of institutional quality on digital financial inclusion in emerging and developing economies?
3. What is the effect of digital financial inclusion on inclusive growth and poverty in emerging and developing economies?

1.4 Research Objectives

The objectives are directly linked to the research questions. The aim of this study is therefore to:

1. Analyse the relationship between FinTech and financial inclusion in emerging and developing economies.
2. Examine the effect of institutional quality on digital financial inclusion in emerging and developing economies.
3. Investigate the effect of digital financial inclusion on inclusive growth and poverty in emerging and developing economies.

1.5 Scope and Limitations of the Thesis

The study employed various proxies and measures for the variables. The research process followed Camara and Tuesta (2017) to measure traditional financial inclusion using access and usage dimensions. The number of ATMs per 100,000 adults and the number of branches per 100,000 adults were employed as indicators for the access dimension; while the number of *borrowers* from commercial banks per 1,000 adults, number of *deposit accounts* with commercial banks per 1,000 adults, *outstanding deposits* with commercial banks (% of GDP), and *outstanding loans* from commercial banks (% of GDP) were employed for the usage dimension.

This study considered distance, affordability, documentation and trust as indicators of the barriers to financial inclusion. Institutional quality factors such as voice and accountability, regulatory quality, the rule of law, political stability, government effectiveness, and control of corruption were employed. The present study followed Khera et al. (2022) to measure digital financial inclusion. Mobile money agent outlets active (per 100,000 adults) and mobile money agent outlets active (per 1,000 km^2) serve as indicators of the access dimension, whereas the number of active mobile money accounts (per 1,000 adults), number of mobile and internet banking transactions (during the reference year) per 1,000 adults, and value of mobile and internet banking transactions (during the reference year) (% of GDP) serve as indicators for usage.

Due to the lack of poverty data in the selected countries, this study employed household consumption expenditure as a proxy for poverty. This study uses GDP per capita as a proxy for inclusive growth. The greatest challenge experienced by the study was lack of data, as a result, some countries were not included in the thesis.

1.6 Thesis Outline

The outline of the thesis is as follows:

Chapter 1: provided the study's foundation by exploring the background, defining the research problem, articulating the questions and objectives, highlighting the study's significance, and delineating its scope and limitations.

Chapter 2: examines the relationship between FinTech and financial inclusion in EMDEs, employing the PCA approach and the system-GMM estimation technique. The System GMM offers reliable and effective estimates, solves the endogeneity issue, and better fits panel studies. This study identifies common issues and future opportunities by looking at how FinTech affects financial inclusion in various EMDEs. Then, it offers recommendations to policymakers and governments. The chapter also identifies the various factors that affect barriers to financial inclusion in EMDEs.

Chapter 3: examines the effect of institutional quality on digital financial inclusion in EMDEs. The chapter employs the panel autoregressive distributed lag (ARDL) as the main estimation technique to determine the short and long-run cointegration between institutional quality and digital financial inclusion in EMDEs. Findings from the study can benefit policymakers and governments in EMDEs to channel capital to appropriate initiatives that can strengthen financial institutions and drive digital financial inclusion.

Chapter 4: investigates the effect of digital financial inclusion on inclusive growth and poverty in EMDEs. The study employed the System-GMM technique to determine the effect of digital financial inclusion on poverty through the intervention of inclusive growth in EMDEs. The findings from the study will help in determining pertinent approaches that relevant stakeholders can use to increase inclusive growth and reduce poverty through digital financial inclusion.

Chapter 5: presents the summary, conclusions, policy recommendations, and directions for further studies.

1.7 Concluding Remarks

This chapter laid the groundwork for understanding the critical role of FinTech and financial inclusion in EMDEs. It began by establishing the context, highlighting the concerted efforts of international agencies and initiatives to leverage FinTech for expanding financial services to underserved populations. The chapter underscores the global recognition of FinTech's potential to bridge financial inclusion gaps, driven by the increasing internet and mobile penetration in EMDEs, and the projected economic benefits of digital financial services.

The significance of digital finance as a tool for poverty reduction and economic advancement was emphasised, with a focus on institutional quality as a key determinant of its effectiveness.

The chapter explored how robust regulatory frameworks, public trust, and infrastructure development are essential for fostering a conducive environment for digital financial services. Furthermore, it highlighted the impact of digital financial inclusion on poverty reduction through inclusive growth strategies, acknowledging the limitations of solely relying on economic growth to address inequalities.

The problem statement highlighted the need for a comprehensive, cross-country analysis of FinTech's impact on financial inclusion, the influence of institutional quality on digital finance, and the role of digital inclusion in poverty reduction. This study uniquely contributes to the existing literature through its cross-country analysis of EMDEs, its integration of barriers to financial inclusion, its digital perspective on financial inclusion, its methodological innovation in index construction using PCA, and its exploration of the relationship between digital financial inclusion, poverty, and inclusive growth. The next chapter focuses on the relationship between financial technology and financial inclusion in emerging and developing economies.

CHAPTER 2

THE RELATIONSHIP BETWEEN FINANCIAL TECHNOLOGY AND FINANCIAL INCLUSION IN EMERGING AND DEVELOPING ECONOMIES

2.1 Introduction

Financial inclusion eradicates poverty, fosters inclusive growth, and strengthens financial stability. Several international institutions, such as the World Bank, the Global Partnership for Financial Inclusion (GPFI[2]), and the United Nations have taken a keen interest in fostering global financial inclusion due to its ability to increase inclusive growth, alleviate poverty, and improve access to digital financial services. An inclusive financial system has various benefits, decreasing the financial intermediation cost for FinTech providers and banks and improving access to financial services and products for poor households (Ozili, 2018). Financial inclusion also provides access to financial services such as digital payments, savings, and solutions for risk management to customers with a range of needs (World Bank, 2021). Lastly, financial inclusion empowers women and the underprivileged to become more economically independent and actively participate in the formal financial system (Siddik, 2017).

2.2 Persistent Global Financial Exclusion in Emerging Markets

Despite these benefits, financial exclusion remains a global problem in Emerging Markets and Developing Economies (EMDEs). The latest 2021 World Bank report states that although 1.4 billion adults remain unbanked, this number has declined from 1.7 billion in 2017. The report further states that almost all the World's unbanked adults live in developing economies, and about 54% of them live in just seven economies, namely, India (17%), China (9%), Pakistan (8%), Indonesia (7%), Nigeria (5%), Egypt (4%), and Bangladesh (4%). This is a testament that financial exclusion is indeed prevalent in EMDEs.

Although financial institutions such as banks provide various financial services and products, many still lack access to these essential services (Beck et al.,2007; Ismael & Ali, 2021; Ozili, 2018). According to Isukul and Tantua (2021), the methods employed by traditional financial institutions in dealing with the problem of financial exclusion in EMDEs are limited and ineffective. For instance, most bank branches are in cities and towns, restricting rural residents

[2] GPFI is a forum where all G20 countries can work together to advance the cause of financial inclusion.

from formal financial products and services. Moreover, essential financial services, such as deposits and loans, offered by traditional banks are sometimes considered too expensive for low-income individuals, and this further serves to solidify exclusion. FinTech has been regarded as a critical tool that can help drive financial inclusion, as it can lower the cost of service for banks through the branchless technology-based banking system. Ozili (2018) argues that FinTech stands for "financial technology," and it is simply the accessibility of financial services and products through cutting-edge technology driven by computer algorithms and programmes. FinTech can improve access and usage of essential financial services, particularly for individuals previously excluded from the formal financial sector.

According to Ozili (2018), digital finance (FinTech-enabled finance) providers in EMDEs positively impact financial inclusion, providing access to individuals with low and variable income and affordability and convenience. Similarly, Lauer and Lyman (2015) and Suri (2017) have established that FinTech enhances financial inclusion and provides the previously unbanked market access to essential financial services. Thus, FinTech continues to be regarded as a critical enabler of financial inclusion. However, Buckley and Webster (2016) argue that FinTech initiatives have been primarily concentrated in developed countries rather than EMDEs. Due to low-income levels and geographical barriers, EMDEs have unique difficulties concerning achieving financial inclusion. Therefore, studies must focus on EMDEs.

Given the importance of FinTech, FinTech-based start-ups are using technology to develop and transform how banking is done globally. FinTech is fast growing as a trend in the global financial industry, and its innovations have the potential and ability to produce a more secure and inclusive system (United Nations Environment Programme [UNEP], 2016). Moreover, FinTech is expected to continue advancing innovative resolutions quicker than traditional banks. In many developing economies, the penetration of financial services has increased due to the recent emergence of digital banking services (DFS) like mobile money (Demirgüç-Kunt & Klapper, 2012).

New entrances of mobile money providers and other FinTech operators across different countries and regions suggest a rise in the adoption of technology in the financial sector. The impact of FinTech in enhancing access to financial services has not yet been adequately quantified, despite financial institutions beginning to adopt technology (Khera et al., 2021). Consequently, examining financial inclusion through FinTech could provide a thorough assessment of the progress of EMDEs.

Emerging market economies have been increasing their investments in FinTech innovation, primarily through infrastructure development and relaxed regulations. Many have also established start-up hubs, accelerators, incubators, and public-private partnership programs (e.g., Start-Up Chile, Start-Up Brazil, and IncubAR in Argentina) to provide FinTech start-ups with funding, technical help, and networking (Alliance for Financial Inclusion Report [AFI], 2019).

The extant literature illustrates that the relationship between FinTech and financial inclusion has mainly been focused on countries or regions at a time. That is, there has not been much attention on simultaneously examining this relationship in several EMDEs. For instance, in most African countries, FinTech has had an overall positive impact on financial inclusion (Kim, 2022; Tiony, 2023; N'dri & Kakinaka, 2020). According to the 2021 World Bank report, account ownership in Sub-Saharan Africa has mostly been driven by mobile money.

2.2.1 Disparities in Financial Access

Despite notable advancements in this region, adults from historically disadvantaged backgrounds continue to face disparities in financial access (Demirgüç-Kunt et al., 2021). While empirical research suggests that Fintech has also had a positive impact on financial inclusion in Asia (Erlianta et al., 2021; Rosyadah et al., 2021; Qamruzzaman & Wei, 2019), most of the unbanked adults are based in China and India. Empirical findings in the Middle East region are mostly positive and show that FinTech drives financial inclusion (Al-Smadi, 2023; Qamruzzaman, 2023). Existing literature also indicates that individuals who were previously unable to access financial services and products are now able to do so due to the impact of FinTech.

However, there is still room for growth as some areas are still financially excluded. Although EMDEs face some similar challenges regarding financial inclusion, their circumstances and needs might differ greatly. Examining the EMDEs collectively rather than individually enables the discovery of specific challenges that are unique to regions that FinTech could address across a variety of scenarios. Moreover, by analysing the EMDEs concurrently, information sharing is facilitated, thus enabling countries to leverage successful FinTech solutions from other countries to address their challenges.

While the primary barriers to financial inclusion in different countries and regions have been identified by the World Bank, most studies that have examined the relationship between FinTech and financial inclusion have not incorporated barriers to financial inclusion in their analysis. As a result, factors that impact barriers to financial inclusion are not discussed in the studies in the empirical literature. Examining the factors that impact barriers to financial inclusion provides insights into the unique challenges encountered by various countries and regions, leading to suitable solutions.

2.3 Purpose of the Study

In essence, there is limited research on the relationship between FinTech and financial inclusion in EMDEs simultaneously according to the author's knowledge. Moreover, the factors that impact barriers to financial inclusion in EMDEs have not been incorporated in most studies. The analytical techniques employed in this study sought to empirically address two questions:

1. What is the relationship between FinTech and financial inclusion in EMDEs, particularly in Africa, Asia, the Middle East, Eastern Europe, Latin America, and the Caribbean?

2. What are the factors that impact barriers (that is, quality) to financial inclusion in EMDEs?

2.4 Contribution of the Study

Considering the gaps highlighted above, this study contributes to the body of knowledge in the four manners outlined below:

2.4.1 Utilisation of Several Econometric Techniques

When compared to earlier empirical studies, this study's unique contribution is its utilisation of several econometric techniques to concurrently examine the relationship between FinTech and financial inclusion, as well as factors that impact barriers to financial inclusion in EMDEs. The study started by employing principal component analysis (PCA) to construct a new financial inclusion index. Constructing a financial inclusion index allows for the assessment of these countries over time. Given that this study used dynamic panel data to estimate the

relationship between FinTech and financial inclusion, the System-Generalized Method of Moments (GMM) was employed as the main technique. System GMM offers reliable and effective estimates, solves the endogeneity issue, and better fits panel studies. Further, for purposes of completeness, this study employed several alternative estimation techniques such as Ordinary Least Squares (OLS), fixed effects (within group estimator), and random effects.

2.4.2 Geographical Focus

This study examined the impact of FinTech on financial inclusion in EMDEs in Africa, Asia, the Middle East, Eastern Europe, Latin America, and the Caribbean, as these regions have a higher prevalence of financial exclusion and thus require more attention. By examining the impact of FinTech on financial inclusion in various EMDEs simultaneously, this study uncovers prevalent problems and potential opportunities and makes recommendations to policymakers and governments.

Through a cross-country analysis, the study investigates factors that impact barriers to financial inclusion in EMDEs. This is essential as it will help policymakers, governments, and organisations comprehend the challenges faced by individuals when accessing financial products and services. Moreover, analysing these factors aids in the development of focused interventions and policies that reduce poverty, foster inclusive financial systems, promote economic growth, and enhance the general well-being of EMDEs.

2.4.3 Use of Panel Data

This study employed panel data – regarded as a superior data set relative to the time series and cross-sectional data settings since it considers both time series and cross-sectional aspects of the data set (Ozturk & Ullah, 2022). Furthermore, panel studies are more beneficial as they gather data from EMDE countries over time, allowing for the extraction of useful information during the analysis. This enhances research rigour.

Examining the relationship between FinTech and financial inclusion and factors that impact barriers to financial inclusion in EMDEs will guide policymakers and governments in deciding where and how to direct initiatives to increase financial inclusion in the different jurisdictions. The study found that FinTech has a significant positive effect on financial inclusion. When FinTech increases by a percentage point, the financial inclusion index will increase by 0.1772

units. This suggests that when individuals accept and adopt FinTech, they will have access to financial products and services, thus, they will be included in the financial landscape.

2.4.4 Mechanisms to Overcome Barriers to Financial Inclusion

There is hope and aspiration that recent innovations in FinTech will offer unprecedented opportunities to overcome barriers to financial inclusion and close the remaining gaps in ownership and use of bank accounts (or accounts at a financial institution), by taking advantage of the increasing penetration of mobile technology (AFI, 2018). Increasingly, FinTech is seen as a key enabler of financial inclusion, and mobile financial services as the type of FinTech with the greatest potential to bring the remaining under-banked into the formal financial system and, ultimately, to achieve more equitable growth (Demirgüç-Kunt et al. 2018; GPFI 2016).

On the control variable, broad money to GDP was found to have a significant and positive effect on financial inclusion in EMDEs at a 5% significance level ($\alpha = 0.05$). The sign and magnitude suggest that a percentage point increase in broad money to GDP leads to an increase in financial inclusion by 0.2761. Inflation as a control variable significantly and negatively affects financial inclusion in EMDEs. In other words, there is an inverse relationship between inflation and financial inclusion. For a percentage point increase in inflation, financial inclusion will decrease by 0.0003.

2.4.5 Analyses of Factors Impacting Barriers to Financial Inclusion

Regarding factors that impact barriers to financial inclusion, the study found that GNI per capita impacts barriers to financial inclusion at a 10% significance level ($\alpha = 0.10$). Thus, an increase in household income makes it easier for households to afford and have access to more essential financial products and services. Higher household income enables households to invest, borrow, and save more money, thus increasing demand for essential financial products and services, such as loans, investment products, savings, and insurance. Hence, an increase in household income makes it easier for households to afford and have access to more essential financial services and products.

Additionally, education was found to impact barriers to financial inclusion. Education provides individuals with financial knowledge, which then enables them to steer clear of exploitative practices. Finally, the broad money-to-GDP ratio was found to be positively significant. When

broad money to GDP increases, financial institutions, such as banks, have more money to lend out. Ultimately, this leads to a decrease in interest rates charged on loans, making it easier for households to afford and have access to essential financial services and products.

This chapter establishes the significance of FinTech and financial inclusion through a review of existing literature, followed by a conceptual framework grounded in both theoretical and empirical analysis. The employed methodology is then detailed, leading to a comprehensive data analysis using various estimation techniques and a discussion of the subsequent findings and their implications. Finally, the chapter concludes with a summary of the analysis and offers recommendations derived from the research.

2.5 Literature Review

It is crucial to review the academic literature and research published in financial inclusion and FinTech, as these two concepts play an essential role in the economy – hence the growing interest in these areas. This study investigated the relationship between FinTech and financial inclusion in EMDEs. Therefore, it is essential to have in-depth knowledge regarding financial inclusion and FinTech and the pertinent research published on these two topics. The empirical literature is thus divided into the following subsections.

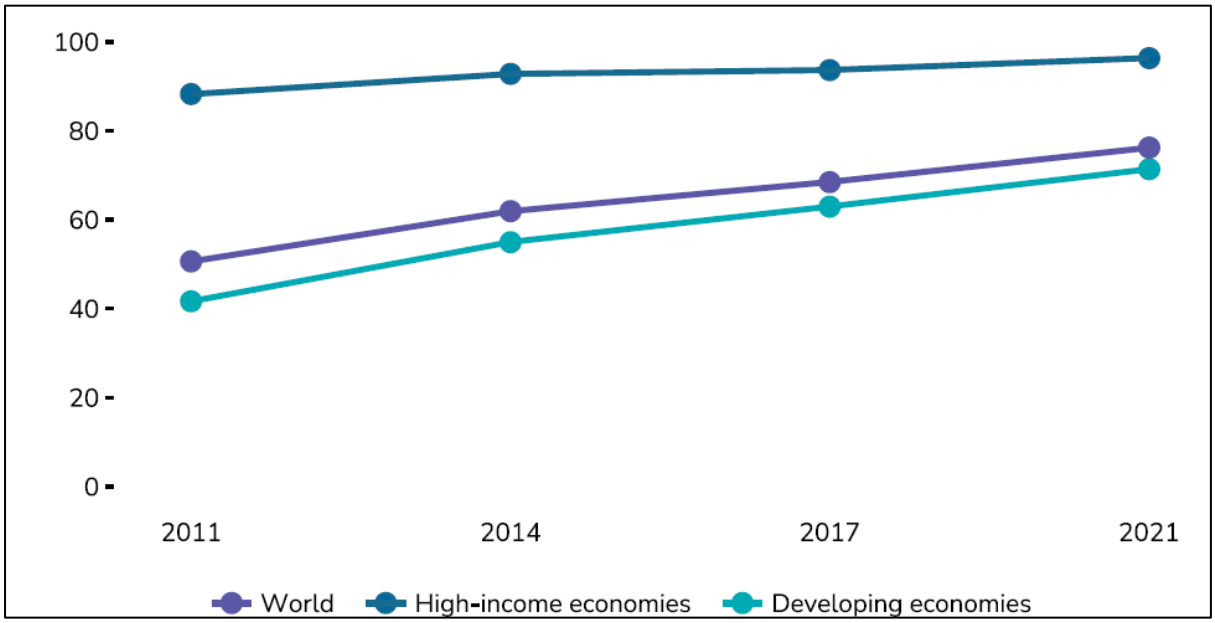
2.5.1 The Concept of Financial Inclusion

Financial inclusion is a critical driver of economic growth and poverty eradication, particularly in EMDEs, as this is where poverty is most prevalent. Notably, financial inclusion helps in narrowing the inequality gap between the rich and the poor. More than 90% of unbanked individuals who lack access to or use formal financial services and products are based in EMDEs. Therefore, increasing financial inclusion is one of the primary concerns EMDEs must urgently address (Demirguc-Kunt et al., 2018). This phenomenon has attracted significant interest from researchers, policymakers, global institutions such as the World Bank and the UN, and other economic stakeholders.

Financial inclusion begins at its most fundamental level with owning a deposit or transaction account with a bank or any other regulated financial institution that can save, send and receive payments, thus enabling account holders to invest in their enterprises, education and health (Demirgüç-Kunt & Singer, 2017). Figure 2.1 (which follows) illustrates a 2021 global Findex

survey from the World Bank, which found that 76% of adults worldwide now have accounts. In EMDEs, account ownership increased by 30% to 71% in 2021 from 42% in 2011. This is an increase of about 50% over 10 years from 2011 to 2021. The survey also established that the growth in account ownership was due to mobile money, especially in EMDEs.

Figure 2. 1: Adults with Bank Accounts



Source: Global Findex Database 2021.

It is important to define the term "financial inclusion," how it is measured, and the various barriers documented in existing literature before we discuss the benefits and impact of financial inclusion in greater detail.

Although financial inclusion has increasingly become a prominent topic in financial literature, no universally agreed-upon definition exists since financial inclusion is a multidimensional concept (Tita & Aziakpono, 2017). International organisations have different definitions. For instance, the World Bank (2021) defines financial inclusion as individuals and organisations having access to useful and inexpensive financial services that satisfy their needs and are provided in a manner that is sustainable and responsible. The United Nations (2016) defines financial inclusion as the provision of inexpensive financial services that enable poor individuals to participate in the formal economy. Even among researchers, different definitions exist. For instance, Mohieldin et al. (2011) define financial inclusion as the ability of low-income segments of society to deliver financial services at an affordable cost.

This definition has been extended to capture and include the use and access of quality financial products at reasonable prices in an appropriate manner, delivered by various service providers in a steady and competitive environment (Financial Inclusion Progress Report, 2015). Allen, Demirgüç-Kunt et al. (2016) and Ozili (2018) define financial inclusion as the process of ensuring that individuals, particularly the poor, have access to essential financial services in the official financial sector. Although these definitions differ somewhat, they all encompass similar aspects of financial inclusion. Further, a financial system is considered inclusive if people access and use financial services and products that satisfy their financial requirements (Ahamed & Mallick, 2019; Corrado & Corrado, 2017; Sanderson et al., 2018).

2.5.2 Measurement of Financial Inclusion

To date, there has yet to be a consensus on how to measure financial inclusion. The lack of consensus on measuring financial inclusion makes it challenging to manage it, particularly in EMDEs. Existing literature illustrates barriers such as lack of universal definition and inconsistent data as challenges observed when measuring financial inclusion (Cámara & Tuesta, 2014; Sarma, 2008). This inability to measure and manage financial inclusion results in dire conditions for poor and underserved individuals. The extent and impact of financial exclusion may be underestimated in the absence of a proper financial inclusion measure. This may result in financial exclusion and not receiving adequate attention, thus leaving households in fragile financial circumstances.

Consequently, the literature proposes various measures of financial inclusion. Beck et al. (2007) were the first researchers who attempted to measure the level of financial inclusion across various countries. The authors mainly focused on access and usage as dimensions and corresponding indicators such as Automatic Teller Machines (ATMs), bank branches, loans, and deposits. Honohan (2008) assessed the degree of financial inclusion by measuring the number of adults with access to traditional financial services and products such as bank accounts. Further, new indicators were established to measure the degree of risk management, savings, payments, and borrowings of adults (Demirgüç-Kunt & Klapper, 2012; Demirgüç-Kunt et al., 2015; Demirguc-Kunt et al., 2018). However, financial inclusion is a multidimensional concept; thus, using indicators such as ATMs, deposits, and bank account ratios to establish the degree and effect of financial inclusion may result in inaccurate information (Camara & Tuesta, 2014; Sarma, 2008) as these indicators only focus on the access dimension and not the usage dimension as well.

Sarma (2008) was one of the first researchers to apply the non-parametric approach in a research study to measure financial inclusion. For the non-parametric methodology, weights of the dimensions are assigned subjectively by the researcher. Sarma (2008) developed a financial inclusion index for 100 developed and developing countries based on 2004 data from the World Bank, IMF, and International Financial Statistics (IFS). The research used three dimensions: penetration, availability, and utilisation. The recommended index enhanced the indexing methodology employed by the United Nations Development Programme (UNDP) to produce the Human Development Index. Sarma and Pais (2011) used availability, access, and usage dimensions to measure financial inclusion for their index. The cited scholars assigned varied weights to the indicators and dimensions based on their judgment. The contribution of the indicators and dimensions in explaining variances in data may differ from the relative weights assigned by non-parametric indexing, potentially resulting in indexing bias.

Although most studies have used different methods to construct a financial inclusion index, most adopt Sarma's methodology, which allocates equal weight to all dimensions (Borhan et al., 2021; Sarma, 2008). Amidzic et al. (2014) contribute to the literature by developing a financial inclusion index using the factor analysis (FA) approach, which allocated weights to each recommended dimension instead of assuming equal weights. Some studies have used a PCA (Camara & Tuesta, 2014; Nuzzo & Piermattei, 2020). For instance, using 2011 to 2014 data, Datta and Singh (2019) constructed a financial inclusion index for several developed and developing countries and investigated its relationship with the Human Development Index. The study also examined the causes of differences in the observed financial inclusion index. The weights for the financial inclusion index's three dimensions (availability, access, and usage) were calculated using PCA.

2.5.3 The Concept of FinTech

Like financial inclusion, FinTech lacks a unified definition. The Financial Stability Board (2022, para.1) defines FinTech as "technologically enabled financial innovation that could result in new business models, applications, processes, or products with provision of financial services," Leong and Sung (2018) define FinTech as a concept that integrates finance, technology management, and innovation management. The CFA Institute (2022) defines it as technological development in the creation and delivery of financial services. While there is no universally accepted definition of FinTech, it is widely agreed that it includes all products,

services, technology, and/or infrastructure that enable individuals and businesses to access essential financial services.

Digital finance (FinTech-enabled finance) can be used to increase access to financial services and enhance economic advancement in underdeveloped markets (Shen et al., 2021). According to the 2015 Consultative Group to Assist the Poor report, digital financial inclusion can be defined as excluded and underserved populations having access to and use of essential financial services through a tech-enabled platform. Similarly, Ebong and George (2021) define digital financial inclusion as a broad term that refers to different forms of financial services and products that can be accessed and delivered through digital platforms. Payments, credit, savings, remittances, and insurance are examples of financial services. The World Bank (2014) defines digital financial inclusion as the deployment of cost-effective digital methods to reach the underserved and financially excluded communities with a range of formal financial services that are catered to their requirements and provided at an affordable cost to customers and viable for providers.

A digital economy promotes economic growth and productivity (Dahlman et al., 2016). A study by Sy et al. (2019) underscores FinTech's potential to improve and accelerate advances achieved in EMDEs in the past two decades. Khera et al. (2021) note that FinTech improves access to essential financial services, particularly in EMDEs. FinTech activities are grouped into five categories: payments, clearing and settlement; deposits, lending and capital raising; insurance; investment management, and market support (Financial Stability Board, 2017).

2.5.4 The Impact of FinTech on the Financial Industry

FinTech is characterised by accelerated expansion, leading to transformative changes in the financial industry across the globe, and its innovations have the potential and ability to produce a more secure and inclusive financial system (UNEP, 2016). FinTech start-ups use technology to develop and transform how banking is done internationally. This trend is expected to continue advancing innovative resolutions quicker than traditional banks. In many EMDEs, the penetration of financial systems has improved because of the recent deployment of mobile money and other DFS (Demirgüç-Kunt & Klapper, 2013).

FinTech has garnered the attention of stakeholders (such as policymakers and academics) in recent years as a possible pathway to financial inclusion. The FinTech revolution has created

new avenues for financial inclusion. This is particularly true in the use of digital currency, mobile accounts, and the issuance of biometric smart cards (Ebong & George, 2021; Naumenkova et al., 2019). Digital Financial Services (DFS) have recently emerged as key facilitators of financial inclusion in EMDEs (Khera et al., 2021).

The adoption of FinTech is increasing variably across geographical regions and countries, with mobile money providers and other FinTech companies making their first advances into the financial industry. Several studies show a relationship between mobile money access and usage and growth in savings, borrowings, transfers, and remittances (Bharadwaj et al., 2019; Lyons & Kass-Hanna, 2021). Similarly, Nguyen (2020) observed that for many households in developing countries, mobile accounts have become a convenient method of executing financial transactions.

FinTech can expedite the distribution of financial services to a proportion of the population (particularly to those who are unbanked). This can be accomplished by utilising cutting-edge technology at a reasonable cost and in a safe setting (Siddiket al., 2020). Comparably, in an earlier study, Ozili (2018) argues that financial services users, digital finance providers, governments, and the economy at large benefit from FinTech (digital finance) and financial inclusion.

In 2021, approximately 4.9 billion people used the internet. This implies that roughly 63% of the world's population is now online (up by 17%). However, 2.9 billion people in the world still do not have access to the internet, with 96% of them living in EMDEs. Furthermore, in 2021, the global penetration of mobile cellular subscriptions increased. Developing nations in Asia, the Pacific, and the Americas drove the growth. In Africa, on the other hand, mobile cellular subscriptions decreased (International Telecommunication Union, 2021). Nonetheless, the banking and telecommunications sectors have taken advantage of the increased usage of cell phones to pioneer the development and uptake of mobile-based FinTech services, particularly money transfers (Ehrbeck et al., 2012). This suggests that FinTech can improve financial inclusion in the above-mentioned regions due to the marked increase in internet and mobile penetration.

The McKinsey Global Institute 2016 report quantified the expected economic impact of FinTech. According to the cited report, the cost of providing financial services can be lowered to 91% by mobile technology. Therefore, one of the main ways to speed up financial inclusion

is expected to be through FinTech. Around 1.6 billion people in EMDEs could be provided access to financial services through DFS by 2025 (Manyika et al., 2016). Thus, DFS are expected to increase the number of new credits granted by USD 2.1 trillion and the number of new deposits by USD 4.2 trillion. Furthermore, the GDP of emerging economies is forecasted to grow by USD 3.7 trillion and generate about 95 million new jobs by 2025 because of DFS (Manyika et al., 2016).

2.6 Theoretical Review

Several theories, frameworks and models have been developed and used in the existing literature to explain user acceptance and adoption of new technologies. These include the Theory of Planned Behaviour (Ajzen, 1985), the Theory of Reasoned Action (Fishbein & Ajzen, 1975), the Diffusion of Innovation Theory (DOI) (Rogers,1962), the Technology Organization Environment Framework (Tornatzky et al., 1990), and Technology Acceptance Model (TAM) as established by Davis (1989).

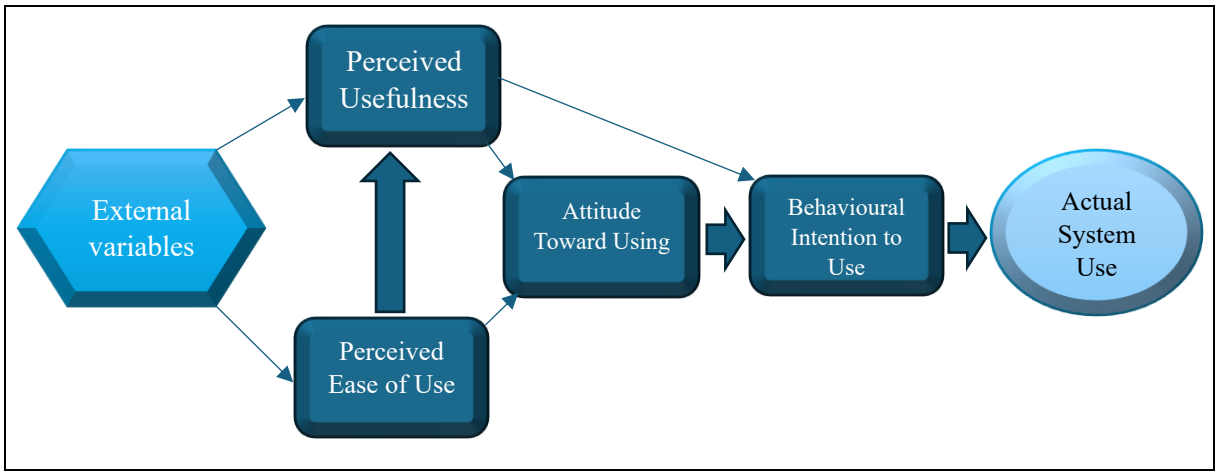
Some studies have affirmed that the TAM is one of the best models used in explaining the acceptance of technology in the context of FinTech (Hu et al., 2019; Meyliana & Fernando, 2019). The TAM and DOI are two of the most widely applied theories for examining the framework of adoption and diffusion of services offered by FinTech (Bureshaid et al., 2021). The assumptions and constructs underlying TAM and DOI are similar in that adopters evaluate innovations based on how they perceive them or that innovations with attractive aspects have a higher likelihood of being adopted (Davis et al., 1989; Moore & Benbasat,1991). Integrating TAM and DOI components could result in a model that is more effective than employing each model separately (Wu & Wang, 2005). When integrating both these models, research has shown satisfactory outcomes (Al-Rahmi et al., 2019).

2.6.1 Technology Acceptance Model

Davis (1989) was the first to develop the TAM, which stems from the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975) in psychological studies. The TAM is the most prominent and widely used theory for understanding technology adoption and acceptance (Yousafzai et al., 2010). The TAM's acceptance is due to its strong theoretical premise and effective frameworks (Chuttur, 2009).

The TAM illustrates how individuals accept and use a particular technology. According to the TAM, three significant factors impact an individual's decision on when and how they will use technology, namely: perceived usefulness (PU), perceived ease of use (PEOU), and attitude towards usage (ATU). Davis et al. (1989) define PU as the degree to which an individual believes a particular system would improve work performance within an organisational environment. Further, PEOU is defined as the degree to which a person feels that utilising a specific system will be easy (Davis et al., 1989). The model's ATU element assesses an individual's affective response to adopting new technologies, while the behavioural intention element encapsulates an individual's intended objectives concerning using new technologies (Davis et al., 1989). Both PU and PEOU are regarded as distinct factors that impact an individual's attitude toward employing a particular technology; however, PEOU is believed to affect both PU and ATU (Masrom, 2007). Other significant factors of the model include behavioural intention to use (BIU) and actual system use (ASU) (Legris et al., 2003). Figure 2.2, below, illustrates the TAM.

Figure 2. 2: Technology Acceptance Model



Source: adapted from Davis et al. (1989)

Several external variables affect PEOU and PU. The TAM is a starting point for investigating the effect that external factors can have on behavioural intentions may have on behavioural intentions (Davis et al., 1989). Both TAM and TRA suggest that external variables indirectly affect behaviour, impacting PEOU and PU in TAM's case or subjective norms in TRA's case (Legris et al., 2003). Despite the empirical validation of TAM and other user acceptance models, researchers continue to add new external variables to these models to increase their explanatory power and limited specificity (Tarhini et al., 2013). Nonetheless, researchers are

continuously developing and evaluating theoretical acceptance models using a variety of external variables (Rahmi et al., 2018).

Several studies have established that integrating TAM with other additional variables helps correctly predict technology adoption amongst various technologies and disciplines. For instance, some studies have included factors such as perceived risk and trust (Ha, 2020; Nguyen & Huynh, 2018; Obaid, 2021; Senyo & Osabutey, 2020) as they pertain to the safety and security of FinTech users and could have a significant impact on individuals that have adopted and use FinTech.

The TAM is widely used due to its simplicity and ease of comprehension (King & He, 2006). However, like many other models, TAM has limitations. For instance, Ajibade (2018) argues that TAM is not practical for businesses, companies, or many organisations that are subject to rules and regulations. However, it is suitable for individual technology adoption and use. In another study, Napitupulu (2017) suggests that TAM ignores social impact and the state of facilities that support user behaviour when using technology. Furthermore, Napitupulu (2017) argues that TAM mainly focuses on technological attributes that are measured in terms of their benefits and accessibility. Notably, the model does not account for internal attributes, while personality qualities are precursors of the cognitive elements of TAM (Agarwal & Prasad, 1998).

2.6.2 Diffusion of Innovation Theory

Although the TAM has been frequently used in earlier studies to clarify how users accept technologies, it is unclear if TAM adequately explains how users adopt various types of technologies (Min et al., 2021). To better understand the rapid changes in innovation, this study employed the DOI theory as an additional framework or theory.

Theories explaining the DOI were first established in the 1920s and the 1930s (Bureshaid, 2021). The DOI theory is one of the most used adoption models, established by Rogers (1962). The DOI has been researched and applied in various disciplines, including sociology, economics, political science, communications, public health, geography, anthropology, and marketing (Rogers, 2004). The cited scholar defines diffusion as a procedure in which innovation spreads over time among the participants in a social system through specific

communication channels. As per the definition, innovation, communication channels, time, and social system are the primary factors of the DOI. These factors are discussed in what follows.

a) *Innovation*

Rogers (2003) describes innovation as an idea, practice, or project that an individual or other adoption unit perceives as new. An idea or product is regarded as an innovation if it is perceived as new by its adopters (Mark & Poltrock, 2001). Therefore, an innovation need not be new, rather, it just must be perceived as new by its potential adopters (Chigona & Licker, 2008). The concept of FinTech is new in many EMDEs, and its novelty perception varies across countries. Despite this perception disparity, the current study focused on DOI adoption of FinTech by individuals who view it as innovative. The DOI asserts that certain attributes of innovation may have an impact on how likely it is that the innovation will be adopted. These attributes are discussed in detail later in the chapter.

b) *Communication Channels*

In communication, individuals develop and exchange information to understand one another (Rogers, 2003). Interpersonal and mass communication media can be used to diffuse innovations (in this case, FinTech); nonetheless, both forms of media serve distinct but complementary functions (Chigona & Licker, 2008). Interpersonal channels are discussions between two or more people, whereas mass media channels include magazine articles, radio, newspapers, television, and social media. While individuals may first learn about innovation through mass communication media channels, judgements regarding adoption are more likely to be influenced by interpersonal communication (Chigona & Licker, 2008; Lowery & DeFleur, 1995).

c) *Time*

Diffusion time focuses on three areas: the rate of adoption, innovation-diffusion process, and adopter categorisation (Rogers, 2003). The cited scholar describes the adoption rate as the speed at which individuals within a social system adopt innovations. For instance, the adoption rate of an innovation can be calculated based on how many people used it for a certain amount of time. The innovation-diffusion process refers to a processing activity in which information is sought and processed, whereby an individual is driven to decrease uncertainty regarding the

benefits and drawbacks of an innovation (Rogers, 2003). The innovation-decision process comprises five phases, which usually follow each other in the order of their occurrence in time. These phases are knowledge, persuasion, decision, implementation, and confirmation. Adopter categories refer to how individuals within a social system are classified according to how innovative they are (Rogers, 2003).

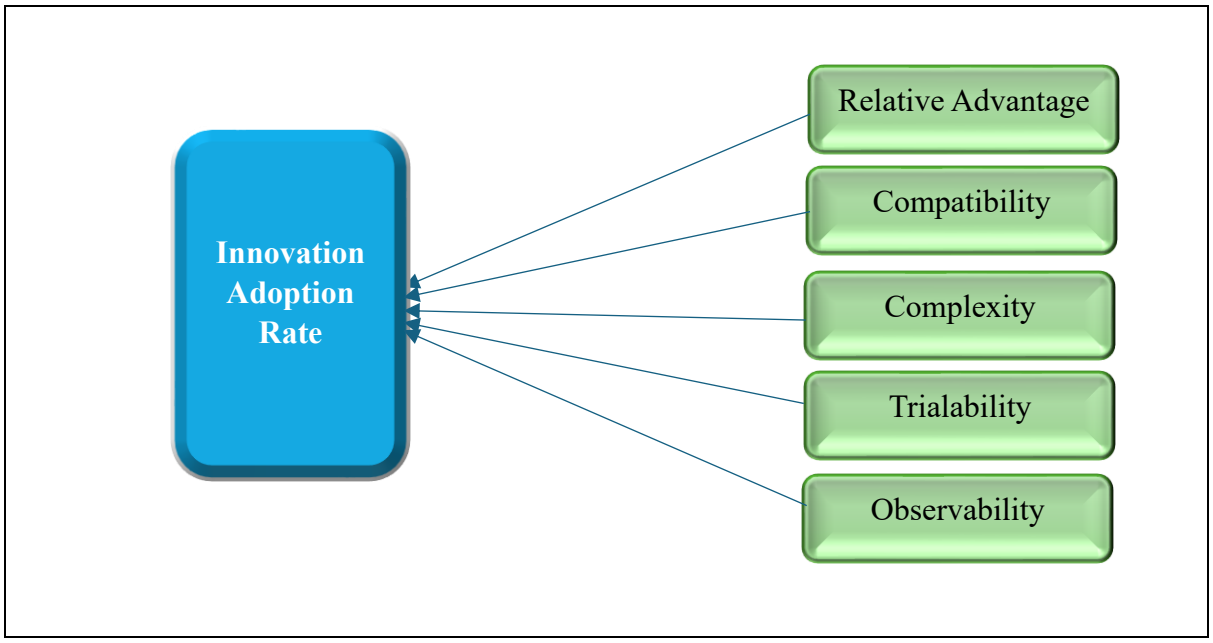
d) *Social System*

A social system is described as a collection of interconnected elements working together to solve problems to achieve a common objective (Rogers, 2003). Diffusion is impacted by the social structures in which the innovation occurs within the social system. For this study, the social systems were EMDEs on which FinTech focuses.

2.6.3 Attributes of Innovations

The DOI can be applied to FinTech and financial inclusion to understand how new financial services and products driven by technology are accepted and adopted by individuals. Rogers (1983) identified *relative advantage, complexity, compatibility, trialability, and observability* as key attributes that significantly impact adoption behaviour. Rogers (2003) further states that individual perception of these attributes contributes to understanding and explaining the adoption rates. These attributes have constantly been identified as the most prominent factors for internet and mobile technology adoption (Sahin, 2006). Rogers also noted that while there is a lot of diffusion research based on the traits of the adopter categories, there is a dearth of studies on how perceived qualities of innovations affect adoption rates. These attributes are illustrated in Figure 2.3, which follows.

Figure 2. 3: Diffusion of Innovation Theory



Source: Adapted from Roger (1983)

a) *Relative Advantage*

Relative advantage is a measure of how much an innovation (in this case, FinTech) is thought to offer advantages over its predecessor. It brings more effectiveness, financial gains, and improved prestige (Monyoncho, 2015). The adoption of an innovation is faster if the perceived relative advantage of the product is high. Customers determine the final assessment of a new tech-enabled (FinTech-enabled) financial service and product's relative advantage by comparing it to the financial services provided by traditional financial institutions.

b) *Compatibility*

Compatibility entails the degree to which implementing the innovation is compatible with what people already do (Kaasinen, 2005). It is the extent to which a new idea is regarded as being in line with the needs, attitudes, and consumer beliefs of previous concepts and experiences (Wani & Ali, 2015). Thus, innovations (in this case, FinTech) that are not compatible with key aspects of the social system will not be embraced and adopted swiftly as compatible ones (David-West et al., 2021). This ultimately affects financial inclusion because if individuals are not familiar and comfortable with new tech-enabled financial services, this will negatively affect the level of financial inclusion in those societies.

c) *Complexity*

Complexity is the degree to which an innovation is difficult to comprehend and use (Roger, 2003). Holak and Lehmann (1990) argue that individuals misunderstand technology due to its complexity. Users are less likely to stick with technology if new technology involves significant learning (Monyoncho, 2015). On the other hand, tech-enabled financial products and services that are easier to comprehend, and use are more likely to be adopted by individuals, thus increasing financial inclusion. Moreover, FinTech's role in financial inclusion could be misunderstood if the advantages of using FinTech are not easily articulated.

d) *Trialability*

As defined by Acharya et al. (2008), trialability is the extent to which innovation (financial inclusion measures) may be tested and experimented with before implementation. Innovations that go through a trial period are more likely to be accepted and adopted since adopters will have less doubt about them.

e) *Observability*

Observability is the ease with which an innovation's effects are observable and communicated to potential users (Rogers, 2003). Innovations that are somewhat harder to observe spread more slowly than those that are more observable.

Although Rogers (1983) further argues that these five attributes increase an innovation's chances of being accepted and adopted, the existing literature demonstrates that often, researchers do not employ all five attributes (Al-Jabri & Sohail, 2012; Hubert et al., 2019; Siddik et al., 2014). There is no consensus among scholars over the application of the five attributes of the DOI theory (Bureshaid & Sarea, 2020). Some studies have applied all five theory's tenets while others have applied only a few. For instance, Al-Jabri and Sohail (2012) used DOI as their foundation to examine factors affecting the adoption of mobile banking in Saudi Arabia. The study found that relative advantage, compatibility and observability positively impact adoption while trialability and complexity have no significant effect.

In another study, Lou and Li (2017) used relative advantage, complexity and compatibility to investigate the adoption of FinTech. Alsheibani et al., (2018) used relative advantage and compatibility to determine a framework for Artificial Intelligence adoption at a firm level. In

contrast, some studies have used all five attributes of the DOI theory in different research fields (Al-Rahmi et al., 2019; Bureshaid & Sarea, 2020; Bureshaid & Sarea, 2021; Mukabi & Vu, 2019).

Comprehending how to apply the Diffusion of Innovation as a theory in FinTech and financial inclusion is important. For instance, although traditional financial institutions such as banks have adopted FinTech, there are still 1.4 billion adults who remain unbanked (World Bank, 2021) and financially excluded. FinTech has been identified as a key driver for financial inclusion. Therefore, the DOI is crucial in understanding the factors that drive FinTech adoption.

Although the theory is helpful in research on technological innovation and its spread, existing literature argues that it has several limitations. The DOI theory has been criticised for its more agrarian approach, which makes it inappropriate for innovations in more technology-focused industries (MacVaugh & Schiavone, 2010). García-Avilés (2020) found that adopters often developed unfavourable sentiments toward cutting-edge innovations in addition to the adoption pattern and rate. Admittedly, the DOI theory has limitations in explaining how innovations are adopted when such innovations cannot be learned by basic modelling (Siddiqui & Adams, 2013). García-Avilés (2020) argued that DOI models often fall short in describing how new technologies are adopted. Instead, due to the complex and networked nature of the technology, the diffusion attributes had to be drastically altered. Notwithstanding its limitations, the DOI has been used by researchers to study the adoption of emerging technologies, especially FinTech services. This shows DOI's widespread use in research.

Financial inclusion in EMDEs depends on FinTech's adoption. Traditional financial institutions, especially banks, need to re-evaluate their business models by integrating suitable innovations to provide a better experience of innovation adoption. Volunteering a particular innovation to people rather than pressuring them to accept and use it produces better results, which raises the possibility that customers will adopt it. Customers' in-person banking experiences have evolved because of FinTech. Customers value access to low-cost, 24/7 online banking and financial services through their smartphones (Moufakkir & Mohammed, 2020), increasing financial inclusion.

Moufakkir and Mohammed (2020) identify why FinTech has been adopted and continues to draw people globally by applying the DOI attributes to FinTech as a financial technological

innovation. There are several benefits of using FinTech, including low cost, efficiency, convenience and 24/7 access to online financial services. In addition, FinTech usage is becoming more voluntary, which has the potential to accelerate adoption and increase financial inclusion.

2.7 Review of Empirical Evidence

This section examines empirical evidence from Asia, Latin America, the Caribbean, the Middle East, and Africa.

2.7.1 FinTech and Financial Inclusion in Asia

A country's economic well-being and progress rely on whether its people have access to essential financial services and products. Asian empirical evidence confirms the relationship between FinTech and financial inclusion. In their research, Rosyadah et al. (2021) investigated the role of FinTech on financial inclusion in Micro, Small and Medium Enterprises (MSMEs) in Makassar. The study used primary data collected through questionnaires delivered both online and offline. The analytical technique employed was linear regression. The researchers found that FinTech has a positive effect on financial inclusion.

Similarly, Erlianta et al. (2021) employed primary data gathered through questionnaires on a sample of 74 SMEs in Palembang City, Indonesia, to examine the effect of FinTech on financial inclusion. The statistical analysis techniques included simple linear regression, coefficient of determination, and hypothesis testing. The linear regression findings revealed a positive and significant relationship between FinTech and financial inclusion. Another comparable study was conducted by Lubis et al. (2019), who investigated how financial inclusion amongst North Sumatran residents was affected by Fintech and financial literacy. The study employed primary data with a questionnaire to sample 100 respondents and multiple linear regression analysis. The results indicate that FinTech and financial literacy have a favourable and significant impact on financial inclusion.

Goswami et al. (2022) examined the essential success elements impacting the adoption of disruptive FinTech for financial inclusion in rural India. The study sample was gathered from six central Indian states determined by the rural population. The study employed exploratory factor analysis and structural equation modelling to assess FinTech's impact on financial

inclusion in rural India. The findings revealed that social influence factors positively affect behavioural intentions to adopt manager technology in India's rural sector.

Using panel ARDL, Granger-causality test, and System GMM techniques, Qamruzzaman and Wei (2019) investigated the relationship between FinTech and financial inclusion for six South Asian countries, namely: Srilanka, Pakistan, Bangladesh, Nepal, Bhutan, and India. The authors used monthly data from January 1990 to December 2018. The findings confirm a positive relationship between FinTech and financial inclusion in the long-run and short-run.

Nurohman et al. (2021) employed the Partial Least Squares (PLS) technique to explore the relationship between financial inclusion, FinTech, and the sustainability of Muslim Small and Medium Enterprises (SMEs) in Solo Raya. A questionnaire was used to gather data from the 96 Muslim-owned SMEs. The findings revealed a positive relationship between FinTech and financial inclusion. There was also a positive relationship between FinTech and the sustainability of SMEs.

Using spatial data techniques, Shen et al. (2021) explored the relationship between digital financial inclusion and economic growth for 86 neighbouring countries. The study also constructed a digital financial inclusion index for a cross-country comparison. According to the findings, digital financial inclusion positively impacts economic growth and spatial spillover effects on neighbouring countries.

Using a two-stage least squares technique, Muganyi et al. (2022) examined the impact of FinTech on different dimensions of financial development in China across 31 provinces and 290 cities. The dimensions used were stability, access, and depth. The study employed panel data spanning from 2011 to 2018. The findings indicated that FinTech positively affects financial development, increasing depth, savings, and access through financial institutions in China.

As already established, FinTech is a powerful tool for fostering financial inclusion, especially in EMDEs, and Asia is no exception. Considering the body of extant literature, it is evident that FinTech has played a crucial role in improving financial inclusion in Asia. Although empirical evidence indicates that financial inclusion in Asia has been positively impacted by FinTech, most unbanked adults are based in China and India. Therefore, gaps must be bridged to ensure financial inclusion.

2.7.2 FinTech and Financial Inclusion in Latin America and the Caribbean

Empirical analysis from most of the existing literature discussed above has provided significant evidence suggesting that FinTech significantly and positively affects financial inclusion. However, there are some regions in which FinTech could have been more helpful in increasing financial inclusion. Gershenson, Gershenson, Lambert, Herrera, Ramos, Rousset and Torres (2021) investigated whether FinTech can reduce financial inclusion gaps in the Latin America and Caribbean (LAC) region and how governments can use FinTech to promote financial inclusion. The study used case studies and a fixed effect model to analyse 2011, 2014, and 2017 data. The outcome of the analysis revealed that the LAC region trails other regions concerning financial inclusion, although there has been a modest improvement since 2011. The study further stated that countries in the LAC region have yet to benefit from FinTech innovations to increase financial inclusion, and drivers of financial inclusion and Fintech-enabled financial inclusion indicate room for improvement.

In a related study, Ioannou and Wójcik (2022) attempted to address the scarcity of research on Latin America's financial geography. The study used financial data, which was quantitative, as well as qualitative information from expert interviews, to investigate the nexus between financial geography and FinTech development, mainly focusing on Mexico, Argentina, and Brazil. The findings showed that although FinTech in Latin America has proliferated, it has evolved on the periphery of the global FinTech sector and the financial industry, with minimal impact on financial inclusion in the region. These two studies indicate that FinTech has not significantly impacted financial inclusion in the LAC region.

On the contrary, findings by Bejar et al. (2022) show that the rapid FinTech growth in LAC countries creates prospects for increased financial inclusion and competition within the banking sector. The study investigated the early impact of the development of Fintech in the LAC region. The study integrated a case study approach and empirical methods such as a difference-in-differences regression and fixed effect panel regression models. The data used spanned 1988 to 2018 and was from the historical balance sheet of 692 banks across nine countries in LAC, namely, Uruguay, Peru, Argentina, Chile, Colombia, Costa Rica, Bolivia, Mexico, and Brazil.

Significant poverty levels and inequality persist in Latin America. Using an unbalanced panel dataset, Limited Information Maximum Likelihood (LIML), and Feasible Generalized Least Squares (FGLS), Ozturk and Ullah (2022) investigated whether FinTech adoption and financial

inclusion reduce the Gini index (inequality) and poverty headcount ratio in 13 Latin American countries. The study found that financial inclusion is essential for combating inequality and poverty. Moreover, the combined effect of FinTech and financial inclusion has the power to reduce inequality and poverty.

Using Brazil as a proxy, Joia and Cordeiro (2021) examined the possibility of FinTech fostering financial inclusion in emerging economies. The study employed the Delphi method, engaging FinTech professionals. The study found that FinTech can serve people who do not have bank accounts, decrease costs through increased competition, and provide financial services to people in remote areas.

There are mixed results on the relationship between FinTech and financial inclusion in the LAC region. Some studies argue that FinTech is still in its infancy and has minimal impact on financial inclusion. On the other hand, some empirical evidence suggests that FinTech has positively impacted financial inclusion. Overall, there is a consensus that FinTech can foster financial inclusion in the LAC region.

2.7.3 FinTech and Financial Inclusion in the Middle East

Focusing on the Middle East and North Africa (MENA) countries, Khalaf and Wadi (2023) explored whether FinTech positively or negatively impacts financial inclusion. Due to availability, the study used data from 2011, 2014, 2017, and 2021 for 11 MENA countries. Further, the study employed the traditional panel regression technique. The findings indicated a positive relationship between FinTech and financial inclusion. Additionally, the results revealed that digital finance improves financial inclusion regarding total account ownership but fails to increase savings account ownership.

Using a system-GMM approach, Al-Smadi (2023) investigated the relationship between digital finance (FinTech-enabled finance) and financial inclusion in the MENA region. A financial inclusion index was constructed using access, usage, and availability as dimensions, while digital finance was proxied by the number of ATMs per 100,000 adults. Annual data spanning 2004 to 2020 for 12 countries in MENA were used. The study found that digital finance improves financial inclusion in the MENA region.

Qamruzzaman (2023) examined how financial innovation impacts financial inclusion in 22 Arab countries using panel data from 2004 to 2020. The study employed the system GMM technique and the Nonlinear Autoregressive Distributed Lagged (NARDL) approach. The findings revealed a significant positive relationship between financial innovation and financial inclusion. Moreover, the research results show that financial innovation adaption and diffusion help provide unbanked individuals access to financial services and products.

Another study by Zalan and Toufaily (2017) examined how participants in the financial sector perceive the impact of digital disruption. Notably, the study explored strategies incumbents adopted for probable disruption from Fintech competitors in the MENA region. The findings revealed that the FinTech sector is still in its infancy stage; however, it is expected to be disruptive in some client sectors and specific products.

Results in the MENA region are positive, showing that FinTech drives financial inclusion. Existing literature also indicates that FinTech provides financial services and products to previously disadvantaged individuals. However, there is still room for growth as some areas are financially excluded.

2.7.4 FinTech and Financial Inclusion in Africa

Empirical evidence shows FinTech's favourable impact on the financial sector, increasing access to financial services (Berkmen et al., 2019; Blancher et al., 2019; Jack & Suri, 2014; Lukonga, 2018). Recent innovative technologies such as machine learning, blockchain technology, the internet, big data, artificial intelligence, and biometric identification have produced new FinTechs such as mobile money, a unified payment interface, and an immediate payment system (Ravikumar, 2019).

Nonetheless, most studies that have assessed the relationship between FinTech and financial inclusion have focused on specific countries (Fanta & Makina, 2019). For instance, Kim (2022) examined how and to what degree mobile money has impacted the financial inclusion levels of women in Nairobi, Kenya. The study used extensive interviews and a structured questionnaire survey to collect data. The findings reveal that mobile money has increased financial inclusion levels by improving women's access to financial services previously excluded from Nairobi.

In another Kenyan study, Tiony (2023) explored how digital financial services (FinTech-enabled services) affect financial inclusion in Kenya. The study relied on various regression models. The findings indicate a significant improvement in financial inclusion, with more individuals being banked and a shift to mobile money platforms such as M-PESA[3]. The study also highlighted digital financial services' economic and empowerment benefits, such as decreased poverty and inequality and better financial resilience. Kim (2022) and Tiony (2023) prove FinTech's positive impact on financial inclusion.

Senyo and Osabutey (2020) argue that insight into the factors preceding the deployment of FinTech innovations will increase financial inclusion. The Ghanaian study used the partial least square structural equation modelling method with survey data from 294 respondents, with Ghana being the study's empirical focus. The results demonstrate that performance and effort expectations substantially impact the decision to use mobile money services.

N'dri and Kakinaka (2020) examined the impact of financial inclusion and mobile money use on people's nonmonetary welfare in Burkina Faso by applying matching methods. The study found that poverty levels decline once individuals access financial services through mobile money. These studies collectively prove that FinTech enables access to financial products and services through innovations such as mobile devices.

Using a different technological innovation, such as the internet, Siddik and Kabiraj (2020) investigated whether digital finance promotes financial inclusion. Two methodologies were employed to examine the effects of digital finance on financial inclusion in the study mentioned above. In the first methodology, 189 countries were examined using data from 2004 to 2016 by conducting a trend analysis with linear regression. The results suggest that financial inclusion increased as the number of internet users increased, indicating a positive relationship between FinTech and financial inclusion. In the second methodology, the authors concentrated on two case studies and found that digital finance (FinTech) positively impacts financial inclusion. The study concluded that FinTech (digital finance) promotes financial inclusion.

In another study, Isukul and Tantua (2021) examined whether the usage of financial technology had improved financial inclusion in five African countries (Ghana, Kenya, Rwanda, South Africa, and Uganda). The researchers approached the study question from a positive

[3] M-PESA is a mobile money service that enables users to send and receive money and deposit and withdraw using their mobile phones.

methodological perspective. The Western philosophical movement known as positivism promoted scientific research methods, claiming that scientific knowledge is readily refutable. The results indicate that FinTech facilitates financial inclusion through innovative instruments, tools, and processes, potentially surpassing the reach and effectiveness of conventional banking methods. Additionally, the study found that FinTech offers more affordable and efficient ways to promote financial development.

Senou et al. (2019) investigated digital technology's rapid impact due to internet usage and phone penetration as dynamic financial inclusion indicators in the West African Economic and Monetary Union (WAEMU) countries. The study employed the random effect model and system GMM for their analysis. Findings suggest that the specific impact of internet usage, phone penetration, and the combined use of the two technologies are crucial to financial inclusion. The cited researchers used data from 2006 to 2017 to first estimate a random effect model, and thereafter, a system GMM technique was employed.

As observed from the empirical literature, several FinTech innovations have been produced and adopted in the African region. This has had a positive impact on financial inclusion. The 2021 World Bank report states that mobile money has been the biggest driver of account ownership in Sub-Saharan Africa. Although there is significant progress in this region, there are still financial access gaps for historically underprivileged adults (Demirgüç-Kunt et al., 2021).

2.7.5 FinTech and Financial Inclusion in Eastern Europe

Panait et al. (2024) primarily sought to understand how digitalization affects financial services and to acknowledge FinTech's global economic importance. To achieve this, the researchers employed regression analysis to investigate the relationship between FinTech in Central and Eastern European (CEE) countries and various digital activities, including Internet usage, online shopping, paying bills online, and digital payment methods. A key finding was the existence of differences in FinTech adoption rates across three distinct groups, or clusters, of CEE nations. The study revealed persistent regional disparities in the availability of new financial products and services across Central and Eastern Europe (CEE). A significant portion of the population struggles with digital tools and new financial providers, which continues to hinder financial inclusion in the region.

Corrado and Corrado (2015) examined the factors that determine financial inclusion (defined as using both banking and credit services) across 18 Eastern European and 5 Western European countries. Using data on 25,000 households from the 2008–2010 Life in Transition Survey, the study finds that households experiencing negative job or income shocks and those lacking assets to use as collateral are less likely to be financially included, a trend particularly notable in Eastern Europe. Furthermore, the likelihood of an individual being included financially is positively influenced by the average use of financial services in their local area, suggesting a financial multiplier effect.

Apostu et al. (2023) assessed the development stage of Fintech in eight Balkan countries (Slovenia, Croatia, Bosnia and Herzegovina, Serbia, Montenegro, Albania, North Macedonia, Bulgaria, and Romania). The study recognizes that the Fintech landscape is diverse due to various factors, including government involvement, EU membership status, and the population's digital and financial literacy. By analysing indicators like internet usage, bank asset share of GDP, and individual financial behaviours (e.g., online banking, digital payments, card ownership), the research found that the Balkan countries are not uniform in their level of Fintech and financial inclusion. These differences are driven by varying public financial policies, the level of IT development, and the population's willingness to adopt new digital financial services.

2.8 Summary of the Empirical Review Findings

The extant literature covers the relationship between FinTech and financial inclusion in developing countries. These studies demonstrated the impact of FinTech on financial inclusion and found mixed results in this regard. Although some studies cited little to no impact, most studies note that FinTech positively affects financial inclusion. Various methodologies and statistical techniques were employed. Interestingly, both primary and secondary data were used in the studies. However, it is crucial to note that while research on this topic is prevalent in many developing regions, there is a significant gap in the literature concerning Eastern Europe and other specific regions within EMDEs. This scarcity of research highlights the need for further investigation into the unique dynamics of FinTech and financial inclusion in these under-explored contexts.

Although financial inclusion is crucial to all countries globally, and FinTech is identified as a critical enabler, the relationship between FinTech and financial inclusion has primarily been

focused on specific countries or regions at a time. The existing literature does not provide a simultaneous cross-country analysis study. Further, although the 2021 World Bank Global Findex report surveys the main barriers to financial inclusion in different countries and regions, most studies that have examined the relationship between FinTech and financial inclusion have not incorporated barriers in their research. Thus, factors impacting financial inclusion barriers are not discussed in the studies cited in the empirical literature surveyed. Moreover, most data analysis techniques are not advanced or efficient.

2.9 Methodology: Modelling FinTech and Financial Inclusion in EMDEs

This section describes the data used and from where it was obtained. It also provides an overview of the variables and techniques employed for the study analyses. This section is divided into four parts: data selection and sources, model specification, measurement of the model, and estimation techniques.

2.9.1 Employing Dynamic Panel Data Analysis

The study starts by using the Principal Component Analysis (PCA) approach to reduce the dimensions of the data. When examining the relationship between FinTech and financial inclusion, previous literature employed static panel data. However, static panel data regressions often fail to address endogeneity issues. This study contributes to the literature by using dynamic panel methods in the analysis. Dynamic panel methods can produce effective estimators even when heteroskedasticity is present and serial correlation and endogeneity are corrected.

Considering that the current study used dynamic panel data to estimate the relationship between FinTech and financial inclusion, the System-Generalized Method of Moments (GMM) is employed as the main technique. Further, for completeness, this study employs several alternative estimation techniques such as Ordinary Least Squares (OLS), fixed effects (within group estimator), and random effects.

2.9.2 Data Selection and Sources

This quantitative study used data generated from secondary sources. This study used annual panel data from 2011 to 2021 in 28 EMDEs due to the availability of data in these regions during this period. Financial exclusion is more prevalent in EMDEs, hence the need to carry

out the study in these regions. Panel data are regarded as a superior data set relative to the time series and cross-sectional data settings since they account for time series and cross-sectional aspects of the data set (Ozturk & Ullah, 2022). The period was selected purely based on the data availability of the chosen variables in EMDEs. Moreover, the starting year for this research is 2011, as some EMDEs chosen for this study did not have available data before 2011. Table 2.1 shows the regions used in this study.

Table 2. 1: Sample Description

Region	No. of Countries in the Region
Africa	12
Asia	2
Eastern Europe	1
Latin America and the Caribbean	11
Gulf Cooperation Council countries/Middle East	2
Total number of countries included in the sample	**28**

Source: Compiled by author

As observed in table 2.1, literature is scarce on the topic in developed countries, hence the Eastern single country sample in Europe. According to the World Bank (2021), 137 of 217 countries qualify as EMDEs, while 80 qualify as developed or high-income countries. Gathering data on the full population of EMDEs was not viable due to economic and logistical constraints. Therefore, secondary data was employed from 28 EMDEs for this study. The following data sources were used: The Global Findex database (Global Findex) of the World Bank, the Financial Access Survey of the IMF (FAS-IMF), and the World Development Indicators (WDI). The data spans from 2011 to 2021.

The Global Findex database contains the most comprehensive information available on how adults save, borrow, pay bills, and manage risk. Since 2011, the database has been published every three years (2011, 2014, 2017, and 2021). The information was gathered from nationally representative surveys of over 150,000 participants across 140 economies. The FAS is a supply-side dataset on access to and use of financial products and services that was introduced in 2009 to help policymakers evaluate and monitor financial inclusion and compare progress to peers. The dataset covers 189 countries and spans more than 10 years. The WDI represents the World Bank's main collection of development indicators, collated from various reputable and reliable international sources. It offers the most recent and reliable global data.

2.9.3 Data Selection, Description, and Measurement of Variables

Data were selected according to the different dimensions and indicators employed by the study. The dependent variable (DV) was *Financial Inclusion.* The following dimensions and indicators were used to measure financial inclusion.

a) *Access (Penetration of Basic Financial Services)*

For financial inclusion to exist, individuals need to have access to essential financial services. This is not only imperative for the financial sector, but it is beneficial to society as well, particularly to low-income earners (Tambunlertchai, 2018). Geographic or demographic penetration is commonly used to assess access. Geographic penetration is favoured since one of the key causes of financial exclusion is the placement of physical access points (Beck, Demirgüç-Kunt & Peria, 2007; Kempson et al., 2004). Therefore, this study used the number of ATMs per 100,000 adults and the number of branches per 100,000 adults as indicators to evaluate access. Data for these variables were generated from FAS-IMF.

b) *Usage*

A bank account is a crucial first step towards financial inclusion. However, to fully benefit from having an account, account holders must be able to use the account securely and conveniently (World Bank, 2017). Traditional banking services and products can be used in a variety of ways, such as payments, deposits, and credit (Ismael & Ali, 2021). Thus, to measure the degree of the usage dimension, this study follows the approach used by Beck et al. (2007), Nguyen (2020), and Sarma (2016). The cited scholars used the following indicators: number of borrowers from commercial banks per 1,000 adults, number of deposit accounts with commercial banks per 1,000 adults, outstanding deposits with commercial banks (% of GDP), and outstanding loans from commercial banks (% of GDP). Data for these variables were generated from FAS-IMF.

c) *The Main Explanatory Variable*

FinTech was the main explanatory variable in the study. FinTech broadly refers to using technology to enhance financial services and products. FinTech is crucial because it can enable accessibility of financial services to people who have historically been underserved by the financial sector. If more people are serviced due to the adoption of FinTech, this could lead to

an increase in financial inclusion. Therefore, a positive relationship is expected between FinTech and financial inclusion. Fintech variables adopted from existing literature were used to construct a FinTech index. These variables are Individuals using the Internet (% of the population), mobile cellular subscriptions (per 100 people), and fixed broadband subscriptions (per 100 people) (Kouladoum et al., 2022; Emara & Mohieldin, 2021). The data were sourced from WDI. FinTech is anticipated to have a positive impact on financial inclusion since it is viewed by many as a tool for an inclusive financial system.

d) *Control Variables*

In line with Nsiah et al. (2021), Emara and Mohieldin (2021), and Okoli and Tewari (2020), the current study further employed the following control variables: Inflation (INF), Trade (% of GDP), General government final consumption expenditure (% of GDP) (GOVEXP), Broad money to GDP, and Gross National Income (GNI) per capita These control variables were obtained from the WDI.

Inflation: This is simply the rate of price increase throughout the economy over a specific period (Chaudhary & Xiumin, 2018). It is used as a measurement of how much the price of a set of products and services has increased over a specific period, typically a year (IMF, 2023). The Consumer Price Index (CPI), which represents a selection of goods and services that households commonly purchase, is the standard unit of measurement for inflation. Financial inclusion can be negatively affected by inflation, especially in EMDEs where there are high rates of unemployment and poverty. For instance, higher bank charges resulting from inflation can make financial products and services less accessible to low-income earners, thus excluding them from the formal financial sector.

Trade (% of GDP): Trade openness refers to the outcomes of a process intended to lower international trade barriers between countries (Mulungula & Nimubona, 2022). Hajilee and Niroomand (2019) argue that the more developed a country's financial market inclusion is, the greater its financial market development and, ultimately, trade openness. Countries with higher trade openness tend to outperform those with lower openness in terms of economic growth as they can benefit from the transfer of technology from well-developed countries (Keho, 2017). A positive relationship between financial inclusion and trade was expected (% of GDP).

General government final consumption expenditure (% of GDP) (GOVEXP): General government final consumption expenditure (% of GDP) encompasses current expenditures for all governments for buying goods and services. Government expenditures have a crucial role in promoting economic growth and the well-being of its citizens (Simatupang, 2020). Government expenditure is typically split into current expenditure and capital expenditure. Current expenditure pertains to the everyday operating expenses of the government. These costs include wages, salaries, supplies, and others.

On the other hand, capital expenditure is defined as spending on assets that are typically long-term, encompassing infrastructure (for instance, schools, roads, and bridges), machinery, and other expenditures that promote a country's economic growth and development (Akanbi, 2019; Poku et al., 2022). Empirical evidence suggests a positive relationship between government expenditure and economic growth in the short run (Poku et al., 2022). Government initiatives that promote financial education and access to digital financial services and products have the potential to effectively drive and increase digital financial inclusion, leading to increased economic growth. A positive outcome is expected for this variable – a positive relationship between government expenditure and financial inclusion.

Broad Money to GDP (Money Supply): The broad money-to-GDP ratio is a measure of the amount of money in an economy relative to its gross domestic product (GDP). Broad money includes demand deposits, other liquid assets, foreign currency deposits, and cash. When the broad money-to-GDP ratio is high, this suggests that there is a large amount of money in circulation in comparison to the size of the economy. Moreover, high broad money to GDP is a sign of economic expansion, and this can have a positive impact on financial inclusion as more people will have access to financial services and products. Thus, a positive relationship is expected between broad money (% of GDP) and financial inclusion. Nwafor (2018) used the broad money-to-GDP ratio to measure the level of financial deepening in Nigeria.

GNI per capita: Gross National Income (GNI) per capita is a metric used to determine the average income of a population of a country. The GNI per capita is a helpful indicator of the development of a country's economy. A positive result is expected because EMDEs already have existing financial institutions in place which people use to access financial services and products. Chima et al. (2021), and Menyelim et al. (2021) used GNI per capita as a control variable in their respective studies.

Table 2. 2: Summary of the Independent Variables' Before Expectational Indications

Variable	Description	Expectation Indication	Data Source
FinTech	Financial Technology	Positive (+)	WDI
INF	Inflation	Positive (+)/ Negative (-)	WDI
BM	Broad Money to GDP	Positive (+)	WDI
GNI	GNI per capita	Positive (+)	WDI
TO	Trade	Positive (+)	WDI
GOVEXP	Government expenditure	Negative (-)	WDI

Source: Author's expectations

2.10 Panel Unit Root Tests

Before beginning the estimation process, this study uses the latest and most effective panel unit roots and cointegration approaches to examine the stationarity of the data. Recent research has demonstrated that panel-based unit root tests are more effective than testing based on time series data as they are less likely to be prone to Type II error (Breitung & Das, 2005; Im et al., 2003; Levin et al., 2002). A type II error is a false negative, which occurs when a false hypothesis is not rejected (Rothman, 2010). The current study used the HD (Hadri, 2000) and LLC (Levin et al., 2002) tests.

a) *The Hadri Unit Root Test*

The null hypothesis of stationarity is the foundation for the test suggested by Hadri (2000). It is a development of the stationary test created in the context of time series by Kwiatkowski et al. (1992), which considers two models: (1) stationary around a deterministic level and (2) stationary around a deterministic trend. Hadri suggests a residual-based Lagrange multiplier test for the null hypothesis that the individual series y_i:t (for $i = 1 \ldots N$) are stationary around a deterministic level or a deterministic trend, against the alternative of a unit root in panel data (Hurlin & Mignon, 2007).

b) *LLC Unit Root Test*

The LLC tests are regarded as first-generation tests that are suitable when cross-sectional units are independent of one another (Westerlund & Breitung, 2013). The main purpose of the LLC test is to determine whether variables are stationary or not (Yüksel, 2017). The LLC test has a null hypothesis that a unit root exists in every panel (Rusike, 2020), while the alternative hypothesis states that all single series are stationary (Mehrara et al., 2011).

2.11 Principal Component Analysis

Following Camara and Tuesta (2014), as adopted by Khera et al. (2021) and Ismael and Ali (2021), the current study employed a two-stage PCA to construct a new financial inclusion index. Constructing a financial inclusion index for EMDEs allows for the assessment of these countries' progress over time. This offers the possibility of comparing financial inclusion levels across countries. PCA is a useful technique to minimise information loss while reducing the number of variables that reflect the same concept (Datta & Singh, 2019).

The PCA technique can decrease data sets to smaller dimensions while retaining as much of the original data as possible. The PCA technique scientifically calculates the weights for each dimension instead of manually assigning them, and it also eliminates the correlated variables that do not contribute to any decision making. Moreover, using a two-stage PCA reduces the likelihood of the PCA being skewed towards the weight of the indicators for a given dimension, ensuring that each indicator is appropriately represented in the analysis.

2.11.1 The Principal Component Analysis Method

This section details the PCA methodology employed to construct the financial inclusion and FinTech indices. PCA was utilised to determine the weights of various dimensions and indicators, ensuring a robust and data-driven approach. The process involved multiple stages, including data normalisation, dimension estimation, and index calculation, ultimately classifying countries based on their financial inclusion levels.

a) *The first stage of PCA*

Estimate the dimensions (access and usage). The present study used indicators for access and usage dimensions (as per the approach of Khera et al., 2021). This essentially means that the two endogenous variables Y^a and Y^u are unobserved for each index and must be estimated using their corresponding parameters (τ and δ) in the equation below:

$$TFI_i = w_1 Y_i^a + w_2 Y_i^u + e_i \quad (1)$$

where TFI is the financial inclusion index of a country i

e_i is the variation due to error

$w_1, w_2,$ represent the weights of each dimension; and

Y_i^a, Y_i^u represent dimensions for access and usage. These dimensions are further computed as:

$$Y_i^a = \tau_1 \text{ATMs} + \tau_2 \text{branches} + e_i \quad (2)$$

$$Y_i^u = \delta_1 \text{borrowers} + \delta_2 \text{deposits} + \delta_3 \text{outstanding deposits} + \delta_4 \text{outstanding loans} + e_i \quad (3)$$

Significant differences exist between country-specific values of the various financial inclusion indicators. Therefore, to improve data comparability, the Min-Max approach is used to normalise the dataset. By subtracting the minimum value and dividing it by the range of the indicators' values, this procedure puts all the distinct indicators within an equal range between 0 and 1(Le et al., 2019). The normalisation formula is presented in equation (5) below:

$$X_{i,d} = \frac{(x_i - m_i)}{(M_i - m_i)} \quad (4)$$

Where x_i indicates the value of indicator *i,* m_i is the minimum value of indicator *i* and M_i is the maximum value of dimension *i*. $X_{i,d}$ represents the standardised value of indicator *i* of dimension *d.*

The estimator of each dimension is represented by the following weighted averages.

$$Y_i^a = \frac{\sum_{j,k=1}^{p} \lambda_j^a PC_{ki}^a}{\sum_{j=1}^{p} \lambda_j^a} \quad (5)$$

$$Y_i^u = \frac{\sum_{j,k=1}^{p} \lambda_j^u PC_{ki}^u}{\sum_{j=1}^{p} \lambda_j^u} \quad (6)$$

The correlation matrix is defined as Rp(pxp) of the p standardised indicators for each dimension. λ_j (j =1,…,p) is described as the j^{th} eigenvalue of each of the dimensions. j represents the number of principal components (PC). The first PC accounts for the greatest degree of variation in the explanatory variables. γj(px1) is the eigenvector of the correlation matrix. The assumption made is that λ1 >λ2 >⋯>λp and represents where P_k (k=1,…,p) as the *k-th PC* (weights).

b) *The Second Stage of PCA*

After getting the dimension indices, another PCA is conducted to determine the weights for financial inclusion. The overall financial inclusion index is computed by combining all the separate indices into equation (1) to estimate the parameter (λ), that is:

$$TFI_i = \frac{\sum_{j,k=1}^{p} \lambda_j PC_{ki}}{\sum_{j=1}^{p} \lambda_j} \quad (7)$$

PC_{ki} (which represents each component) is expressed as a linear combination of the two dimensions and their respective eigenvectors of the correlation matrices as follows:

$$PC_{1i} = \pi_{11} Y_i^a + \pi_{12} Y_i^u \quad (8)$$

$$PC_{2i} = \pi_{21} Y_i^a + \pi_{22} Y_i^u \quad (9)$$

By replacing the PC_{ki} as written in equations (8) and (9), the financial inclusion index can therefore be expressed as

$$TFI_i = \frac{\sum_{j=1}^{3} \lambda_j (\pi_{j1} Y_i^a + \pi_{j2} Y_i^u)}{\sum_{j=1}^{3} \lambda_j} \quad (10)$$

Equation (10) can thus be written as a linear equation for the weighted average of the financial inclusion index:

$$TFI_i = w_1 Y_i^a + w_2 Y_i^u + e_i \quad (11)$$

As per Sarma (2008), the financial inclusion index is then used to classify the various countries into three groups.

$0.5 < TFI \leq 1$ illustrates high financial inclusion.
$0.3 \leq TFI < 0.5$ demonstrates medium financial inclusion.
$0 \leq TFI < 0.3$ shows low financial inclusion.

c) *Indexing FinTech*

$$FinTech_i = w_1 INT_i + w_2 MOB_i + w_3 FFB_i + ei \quad (12)$$

Where; $FinTech_i$ is the index for the i^{th} year and W_1, W_2,…,W_3 are the respective weights of different variables. INT, MOB, and FBB denote the individuals using the Internet (% of population), mobile cellular subscriptions (per 100 people), and fixed broadband subscriptions (per 100 people).

Equations (4) to (11) above are followed and repeated using Fintech variables to construct an index.

2.3.6 Panel Estimation Techniques

The study used the ordinary least squares approach, fixed effects and random effects, and the System-Generalized Method of Moments (GMM).

a) *Ordinary Least Squares Approach*

Three standard models are used for static panel data in research studies. These are constant coefficients (pooled regression) models, random effects models, and fixed effects models. Of the three models, the pooled regression models are the simplest in terms of combining variables over time and across countries while disregarding the time and cross-sectional aspects of the dataset (Gujarati et al., 2012). Due to its failure to control endogeneity and heterogeneity among cross-sectional dimensions, pooled regression models generate biased results (Ozturk & Ullah, 2022). Therefore, researchers often use the fixed effects method when conducting research.

The OLS technique identifies the values of the intercept, β_0, and the slope, β_1, which reduces the sum of the squared residuals. In other words, the OLS technique determines the line that best fits the data by reducing the variables between the independent variable, x_i, and the dependent variable, y_i. According to the Gauss-Markov theorem, the OLS estimator is the Best Linear Unbiased Estimator (BLUE), thus suggesting that it has the least variance relative to other linear estimators that are unbiased.

Moreover, the common coefficients β and θ, and the common intercept Ci are assumed to be effective OLS estimators for the group in pooled regressions. Consider the pooled regression model specified below:

$$TFI_{it} = C_i + \beta FinTech_{it} + \theta X_{it} + \varepsilon_{it} (u_i = 0) \quad (13)$$

$$\varepsilon_{it} = u_i + \varepsilon_{it}$$

u_i denotes the fixed effects, and ε_{it} denotes the error term. The study assumes that μi and εit are exogenous to each other. Therefore,

$$E[\,u_{it}] = [\varepsilon_{it}\,] = [u_{it}, \varepsilon_{it}\,] = 0. \quad (14)$$

A dynamic panel bias is introduced by the presence of the lag endogenous variable as there is a correlation between u_{it} and ε_{it}. The issue of endogeneity arises because of the correlation between one of the regressors and one component of the error term (Nzimande & Ngalawa, 2017). Endogeneity bias can result in erroneous estimates and results, which can lead to false inferences and inaccurate interpretations. The GMM approach can be used to address the endogeneity issue found in OLS models, as it consistently produces reliable results (Ullah et al., 2018).

b) *Fixed Effects and Random Effects*

Fixed effects models assume one true effect size underlying all the studies in the analysis, and that the sampling error is the cause of all the variations in the observed effects (Borenstein et al., 2010). An F-test is used to evaluate the estimation of fixed effects using the Least Squares Dummy Variables (LSDV) method.

With fixed effects models, unobservable country-specific attributes that might be correlated to each country's financial inclusion level can be controlled. Consider the fixed effect regression model specified below:

$$TFI_{it} = C_i + \beta FinTech_{it} + \theta X_{it} + \varepsilon_{it} + u_i \quad (15)$$

C_i and u_i denote the country and annual fixed effects.

According to Clark and Linzer (2015), the fixed effects model will produce unbiased estimates of β although the estimates will be subject to high sample-to-sample variability. The Within Group estimator eliminates the source of consistency by transforming the equation to eliminate u_i. Although the individual fixed effect is eliminated by the within-group estimator, the dynamic panel bias remains unaddressed. This implies that the within-group estimator is also inconsistent & standard results suggest that it is biased downwards (Nickell, 1981).

Although findings from fixed effects estimations are often more reliable than those from conventional OLS regressions, they are not without flaws. There are still valid reasons to be cautious about unobserved time-varying heterogeneity in many applications (Collischon & Eberl, 2020). The disadvantage of using both the Pooled OLS and Fixed effect models is that

they disregard the dynamic part of the model, which could lead to contradictory estimates, particularly in small samples as demonstrated by Nickell (1981). Another related drawback of the fixed effects models is that for each unit, they need the estimation of a parameter. This may lead to a significant decrease in the models' power and an increase in the coefficient estimates standard errors (Allison, 2009).

The random effects models estimate panel data wherein interference variables might be interconnected across time and individuals. The error terms of each country in the random effect model account for the difference in interference (Zulfikar et al., 2018). Greene (2010) argues that the inconsistency resulting from the correlation between the random effect and explanatory variables is the limiting problem with random effects.

c) *System-Generalized Method of Moments (GMM)*

GMM techniques were originally introduced by Hansen (1982), and Holtz-Eakin, Newey, and Rosen further enhanced them (1988), while Arellano and Bond (1991) promoted the Difference GMM. The difference-GMM estimator is developed for data with many individuals but few periods, that is, small T and large N panels.

The system-GMM was then outlined by Arellano and Bover (1995) and extensively developed by Blundell and Bond (1998). The system-GMM formulates supplementary orthogonality conditions that make more valid instruments accessible and achieve efficiency gains. System GMM helps in addressing the problems of heteroskedasticity, bias of omitted variables, endogeneity between variables, and autocorrelation (Ali et al., 2022).

When examining the relationship between FinTech and financial inclusion, previous literature employed static panel data. However, static panel data regressions often fail to address endogeneity issues. Also, considering the issues associated with dynamic panel data and other dynamic panel data estimators, such as first difference and the within-group estimator, this study employs system GMM to estimate the relationship between FinTech and financial inclusion in EMDEs. This is because dynamic panel methods can produce effective estimators even when heteroskedasticity is present and serial correlation and endogeneity are corrected.

This study used the system-GMM instead of the difference-GMM estimator as the system GMM offers reliable and effective estimates, solves the endogeneity issue, and better fits panel

studies. Similar to difference-GMM, the system-GMM estimator is developed for data with many individuals but few periods, that is, small T and large N panels. The system GMM produces estimates that are much more accurate and have a smaller amount of bias relative to the difference of GMM (Blundell and Bond, 1998).

This study's period is from 2011 to 2021, while the number of EMDEs used is 28. Thus, the system GMM was suitable, as alluded to earlier, that N>T to avoid large instruments. The study uses a panel compiled annually. Another way of evaluating whether the estimation technique to be used should be static or dynamic is to check whether the dependent variable is lagged or not and whether it is part of the regressors. If it is lagged, then the suitable approach to be used is dynamic (Gujarati, 2012).

The System-GMM is demonstrated below:
Equation (16) represents the econometric model for determining the relationship between FinTech and financial inclusion.

$$TFI_{i,t} = \beta_0 + \beta_1 FINT_{it} + \beta_2 X_{it} + \varepsilon_{i,t} \quad (16)$$

X_{it} is the vector of exogenous control variables and is further expanded in equations (17) and (18).

Equations (17) and (18) represent the random and fixed effects, respectively, which are static models.

$$TFI_{it} = \beta_0 + \beta_1 FINT_{it} + \beta_2 TO_{it} + \beta_3 GOVEXP_{it} + \beta_4 GNI_{it} + \beta_5 BM_{it} + \beta_6 INF_{it} + u_{it} + \varepsilon_{it} \quad (17)$$

$$TFI_{it} = \alpha_i + \beta_0 + \beta_1 FINT_{it} + \beta_2 TO_{it} + \beta_3 GOVEXP_{it} + \beta_4 GNI_{it} + \beta_5 BM_{it} + \beta_6 INF_{it} + u_{it} + \varepsilon_{it} \quad (18)$$

Equation (19) is used to examine the relationship between FinTech and financial inclusion in EMDEs, using a system GMM.

$$TFI_{it} = TFI_{it-1} + \beta_0 + \beta_1 FINT_{it} + \beta_2 TO_{it} + \beta_3 GOVEXP_{it} + \beta_4 GNI_{it} + \beta_5 BM_{it} + \beta_6 INF_{it} + u_{it} + \varepsilon_{it} \quad (19)$$

where; TFI_{it} represents the traditional financial inclusion index, TFI_{it-1} is the traditional financial inclusion index lag, β is the coefficient of the estimated equation, FINT_{it} denotes the FinTech index, TO_{it} is trade (% GDP), GOVEXP_{it} is the government expenditure, GNI_{it} is GNI per capita, BM_{it} is the broad money to GDP, and INF_{it} is the inflation.

u_{it} is the fixed effect by country, $\varepsilon_{i,t}$ is the error term, *i* is the country index, and *t* is the period (years).

This analysis was performed using the STATA 18 statistical software package. All diagnostic tests, such as autocorrelation and overidentification tests, among others, are conducted in this study. Furthermore, in the empirical analyses, panel-robust standard errors are used since fixed effects estimations with longitudinal data require the estimated standard errors to be adjusted for arbitrary types of serial correlation and heteroskedasticity (Moreno-Serra & Smith, 2011).

2.3.7. Diagnostic Tests

The study used the Sargan test, the autocorrelation test (Arellano-Bond Test), the Heteroskedasticity Test, and a model specification test.

Sargan/Hansen Test for overidentifying restrictions: The Sargan test is used to test for the validity of overidentifying restrictions in the estimation model. The null hypothesis of the Sargan test is that the instruments are valid.

Autocorrelation Test (Arellano-Bond Test): The test for residual correlation is another crucial test for dynamic panel estimation. Autocorrelation is simply a measure that shows how closely related a variable is to its own lagged values. The null hypothesis of the Arellano-Bond autocorrelation tests of the first order (AR1) and second order (AR2) is that there is no autocorrelation in the residuals.

Heteroskedasticity Test: To check for heteroskedasticity, the study used the Breusch-Pagan test. The null hypothesis states that residuals are homoscedastic. The alternative hypothesis states that heteroskedasticity exists.

Model Specification Test: To determine whether the model's specifications are accurate, this study employs the Ramsey Regression Equation Specification Error Test (RESET). The Ramsey RESET test assesses whether there are relationships between the dependent variables

and the independent variables that are non-linear and not explained by the linear structure of the model. The null hypothesis states that the model has no omitted variables.

2.12 Empirical Results and Discussion

This section addresses data analysis and interpretation of all variables estimated in this study and is further divided into five subsections. The results of the PCA used to build the financial inclusion index are explained in the first subsection. The second subsection presents the descriptive statistics as well as various diagnostic tests that were used. Subsection 4 analyses the results of the system GMM used to examine the relationship between FinTech and financial inclusion in EMDEs. Subsection 5 discusses the results of whether barriers to financial inclusion affect the quality of financial inclusion or not.

2.12.1 Descriptive Statistics

Table 2.3 below depicts the descriptive statistics of the variables used to investigate the relationship between financial inclusion and FinTech. The average financial inclusion level for the selected EMDEs over the last decade was low, averaging only 0.2616 with a standard deviation of 0.1132. Nsiah and Tweneboah (2023) support this finding, noting that financial inclusion levels were low across their selected countries between 2004 and 2020. The FinTech mean is recorded at 0.4948, with a 0.1193 standard deviation, signifying a stable variable. Trade (% of GDP) generated a minimum of 45.5401 and a maximum of 85.9546, with a mean of 63.8364 and a standard deviation of 16.3878.

The data show that the selected EMDEs exhibit a considerable variation in their dependence on trade. The mean value of the general government final consumption expenditure (% of GDP) was recorded at 14.4414 with a standard deviation of 2.5104. The average Gross National Income (GNI) per capita is $4864.01 with a standard deviation of $3706.05, thus demonstrating that there is a notable variability in the GNI per capita across the dataset. Broad money to GDP recorded a 50.7402 mean and 14.6768 standard deviations, suggesting that the selected EMDEs maintained a relatively balanced proportion of broad money to GDP with marginal changes over the 10 years. The inflation rate on the selected EMDEs is unstable, with a mean of 7.7101 and a standard deviation of 35.1044. Ha et al. (2019) found that in EMDEs, inflation expectations are less stable than in developed economies.

Table 2. 3: Summary Statistics for the Financial Inclusion Dataset

Variables	Observations	Mean	Standard deviation	Minimum	Maximum
TFI	308	0.2794	0.1798	0.0019	0.6696
FINT	308	0.4927	0.2058	0.0521	0.9174
TO	308	70.2954	34.4665	23.9344	172.8034
GOVEXP	308	15.7200	7.0423	5.0393	40.5535
GNI	308	6158.681	7960.113	421.1765	43995.9
BM	308	53.3769	27.0809	14.3792	140.0924
INF	308	7.7101	35.1044	-2.4309	557.2018

TFI: Traditional Financial Inclusion, FinT: Financial Technology; TO: Trade Openness (%GDP); GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); MS: Broad Money to GDP (Money Supply); INF: Inflation

Source. Calculated by the author using Stata 18

2.12.2 Unit Root Test Results

The study employed the Levin-Lin-Chui (LLC) and the Hadri unit root tests. Both tests indicate that financial inclusion, FinTech, Trade (% of GDP), Government expenditure, Gross National Income (GNI), Broad money to GDP, and Inflation are all stationary at level [I (0)] and trend, indicating that they are valid, reliable and appropriate for the study, and did not generate spurious results. Table 2.4, which follows, shows the results of the unit root tests.

Table 2. 4: Unit Root Test Results for Financial Inclusion Dataset

Variable	Levin-Lin-Chui Unit		Hadri	
	Level		Level	
	Constant	Constant +Trend	Constant	Constant +Trend
TFI	-7.7282***	-11.0500***	24.4430***	7.3820***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FINT	-4.2214***	-10.4418***	29.4497***	18.5515***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
TO	-6.4713***	-11.0104***	16.9420***	4.1004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GOVEXP	-3.9776***	-7.7498***	11.7203***	4.5270 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GNI	-2.6829**	-5.3953***	20.7501***	18.1348***
	(0.0036)	(0.0000)	(0.0000)	(0.0000)
BM	-0.4702	-6.5624***	19.3081***	5.6104***
	(0.3191)	(0.0000)	(0.0000)	(0.0000)
INF	-4.8009***	-11.6478***	9.6775***	1.9058**
	(0.0000)	(0.0000)	(0.0000)	(0.0283)

TFI: Traditional Financial Inclusion, FinT: Financial Technology; TO: Trade Openness (%GDP); GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); MS: Broad Money to GDP (Money Supply); INF: Inflation
Note: () denote the p-values
****, **, denote the significance at the 1% and 5% levels respectively*

Source. Calculated by the author using Stata 18

The Hadri test's null hypothesis (H_0) states that all panels are stationary, while the alternative hypothesis (H_a) states that some panels contain unit roots. The results of the Hadri test show that all variables are stationary at the level. Thus, the null hypothesis could not be rejected. The LLC test's H_0 states that panels contain unit roots, while the H_a states that panels are stationary. The outcome of the LLC test from this study shows that all variables are stationary at the level, therefore, we reject H_0.

2.12.3 Multicollinearity – Variance Inflation Factor

The VIF was employed to test for multicollinearity. The results show that the VIFs of the independent variables as per Table 2.5 (below) are less than 10, indicating no multicollinearity.

Table 2. 5: Variance Inflation Factor Test

Variables	VIF	1/VIF
GNI	1.76	0.5697
TO	1.55	0.6463
FinTech	1.46	0.6858
BM	1.31	0.7647
GOVEXP	1.24	0.8047
INF	1.04	0.9661
Mean VIF	**1.39**	

Source. Calculated by the author using Stata 18
FinTech: Financial Technology; TO: Trade Openness (%GDP); GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); MS: Broad Money to GDP (Money Supply); INF: Inflation

2.12.4 Pairwise Correlation Matrix for Panel Data

This section discusses the correlation between the dependent variable (that is, financial inclusion) and each of the explanatory variables. The pairwise correlation matrix is presented in Table 2.6 below.

Table 2. 6: Pairwise *Correlation Matrix for Panel Data*

	FII	FinTech	TO	GOVEXP	GNI	BM	INF
FII	1						
FinTech	0.6445	1					
TO	0.2726	0.1228	1				
GOVEXP	0.0277	0.0775	0.3738	1			
GNI	0.5809	0.4832	0.4337	0.0042	1		
BM	0.7103	0.3964	0.2429	0.028	0.4068	1	
INF	-0.1308	-0.1361	-0.0507	-0.0914	-0.0877	-0.1374	1

FinTech: Financial Technology; TO: Trade Openness (%GDP); GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); BM: Broad Money to GDP (Money Supply); INF: Inflation

Source. Calculated by the author using Stata 18

Multicollinearity may be a major issue if the zero-order (pairwise) correlation coefficient between two regressors is strong, particularly greater than 0.8 (Imdadullah et al., 2016). None of our selected variables have a correlation coefficient greater than 0.8, thus indicating that there is no multicollinearity between the variables.

The correlation coefficient between financial inclusion and FinTech is 0.64, thus indicating that there is a moderate positive correlation between these two variables. Trade openness (% GDP) is positively correlated to financial inclusion. The coefficient of correlation reveals that there is a weak positive correlation between trade openness (% GDP) and financial inclusion. The results further reveal that General government final consumption expenditure (% of GDP) and financial inclusion have a weak positive correlation with correlation coefficient of 0.03. GNI per capita is positively correlated to financial inclusion. The coefficient of correlation shows that there is a moderate positive relationship between GNI per capita and financial inclusion. Broad money to GDP is positively correlated to financial inclusion. Given that the correlation coefficient is greater than 0.71, this shows a strong positive correlation between broad money to GDP and financial inclusion. Inflation is the only explanatory variable that has negatively correlated to financial inclusion. Inflation and financial inclusion have a weak negative correlation with a correlation coefficient of -0.13.

a) *Heteroskedasticity*

Table 2.7 below demonstrates the results of the Breusch-Pagan test, employed for testing for heteroskedasticity.

Table 2. 7: Heteroskedasticity

Test	Statistic	d.f.	Probability
Breusch-Pagan LM	399.725	378	0.212

Source: Calculated by the author using Eviews 13

The *p*-value of the Breusch-Pagan test is greater than 5%, thus indicating that there is no problem of heteroskedasticity in the data. Consequently, the null hypothesis could not be rejected due to insufficient evidence against it.

b) *Model Specification Test*

Table 2. 8: Ramsey RESET Test for Omitted Variables

Test	Estimate	Df	Probability
Ramsey RESET test for omitted variables	1.27	(3, 298)	0.2856

Source. Calculated by the author using Stata 18

The Ramsey RESET test's *p*-value for omitted variables in Table 2.8 above is greater than 5%, indicating that the model is specified correctly. Therefore, the null hypothesis could not be rejected.

2.13 Estimated Results for Financial Inclusion Index

Before performing the PCA test, it is essential to conduct a Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity. The KMO test is used to evaluate the suitability of the sample size for PCA whilst Bartlett's test of sphericity determines the intercorrelation of the indicators chosen for the study. PCA can be performed if KMO>=0.5 and X^2 (that is, chi-square) in Bartlett's test of sphericity is statistically significant. As illustrated in table 2.6, the KMO test for this study is 0.732, which indicates that the data used for this study is suitable and appropriate. Bartlett's test of sphericity has an X^2 of 1042.927 and a *p*-value of 0.000 which shows that there is no correlation between the selected indicators of the study. Table 2.9 illustrates the results of the KMO test.

Table 2. 9: Kaiser–Meyer–Olkin Measure and Bartlett's Test of Sphericity

Test	Measure	Financial Inclusion dataset
Kaiser–Meyer–Olkin		0.732
Bartlett's test of sphericity	Chi-square	1042.927
	Degrees of freedom	21
	p-value	0.000

Source. Calculated by the author using Stata 18

Using STATA 18, a measuring model for constructing a financial inclusion index was carried out. The access (Y^a) and usage (Y^u) dimensions were used in the measurement model. To ensure that the scale in which they are assessed is irrelevant, indicators of each dimension are standardised to have values that range between 0 and 1 before the PCA is conducted, where 0 shows financial exclusion and 1 illustrates financial inclusion.

Table 2. 10: Principal Components Estimates for Sub-Indices

Component	Eigenvalue	Difference	Proportion	Cumulative
Access dimension				
Comp1 (ATMs)	1.42271	0.84542	0.7114	0.7114
Comp2 (Branches)	0.57729	.	0.2886	1
Usage dimension				
Comp1 (Borrowers)	2.93227	2.28863	0.7331	0.7331
Comp2 (Deposits)	0.643638	0.327072	0.1609	0.894
Comp3 (Outstanding deposits)	0.316567	0.209042	0.0791	0.9731
Comp4 (Outstanding loans)	0.107525	0	0.0269	1

Source. Calculated by the author using Stata 18

The results of the first-stage PCA are illustrated in Table 2.10 above. The eigenvalues of each sub-index and latent variables, access (Y^a) and usage (Y^u) are determined by using the PCA method. Principal components with eigenvalues greater than one are the only ones considered for the analysis, as the component with the highest eigenvalue retains more standardized variance relative to the rest (Kaiser, 1960; Nguyen, 2020). As per Table 2.6, the eigenvalues of the principal components for the two dimensions are as follows: 1.42271, 0.57729 (access); and 2.93227, 0.643638, 0.316567 (usage). None of the other principal components have an eigenvalue greater than one, apart from the first principal (that is, component 1 of the access and usage dimensions). As a result, only the first component is used for the analysis, while the estimations of the dimensions are done using weights allocated to the first component of each dimension.

Table 2. 11: Scoring Coefficients for Orthogonal Varimax Rotation (Weights)

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Unexplained
Access dimension					
No. of ATMs per 100,000 adults (ATMs)	0.7071	0.7071			0
No. of Branches per 100,000 adults (Branches)	0.7071	-0.7071			0
Usage dimension					
No. of borrowers from commercial banks per 1,000 adults (borrowers)	0.4827	0.4795	0.7286	0.0787	0
No. of deposit accounts with commercial banks per 1,000 adults (deposits)	0.485	0.4973	-0.6754	0.2477	0
Outstanding deposits with commercial banks (% of GDP) (Outstanding deposits)	0.4806	-0.6681	0.0603	0.5648	0
Outstanding loans from commercial banks (% of GDP) (Outstanding loans)	0.5484	-0.2764	-0.0969	-0.7832	0

Source. Calculated by the author using Stata 18

The retrieved weights of each of the six indicators are displayed in Table 2.11 above. Considering this, for the access dimension, the weights assigned for the first component are equal to 0.7071 for *No. of ATMs per 100,000 adults'* indicator; and 0.7071 for *No. of Branches per 100,000 adults'* indicator. This means that both ATMs and branches drive the access dimension equally.

On the other hand, for the usage dimension, the *outstanding loans from commercial banks (% of GDP)* indicator has a higher weight at 0.5484 relative to *outstanding deposits with commercial banks (% of GDP)* indicator *at 0.4806, No. of deposit accounts with commercial banks per 1,000 adults'* indicator at 0.485 and *No. of borrowers from commercial banks per 1,000 adults'* indicator at 0.4827. This illustrates that the *outstanding loans from commercial banks (% of GDP)* indicator is more vital than other indicators defining the usage dimension.

By allocating the weights retrieved above to equations (2) and (3) in section 2.3.3.1, equations (20) and (21) for access and usage dimensions are derived, respectively:

$$Y_i^a = 0.7071_{\text{ ATMs}} + 0.7071_{\text{ branches}} + \boldsymbol{e_i} \quad (20)$$

$$Y_i^u = 0.4827 \text{ borrowers} + 0.485 \text{ deposits} + 0.4806 \text{ outstanding deposits} + 0.5484 \text{ outstanding loans} + \boldsymbol{e_i} \quad (21)$$

$$\text{TFI}_i = [0.7071_{\text{ ATMs}} + 0.7071_{\text{ branches}}] + [0.4827 \text{ borrowers} + 0.485 \text{ deposits} + 0.4806 \text{ outstanding deposits} + 0.5484 \text{ outstanding loans}] + ei \quad (22)$$

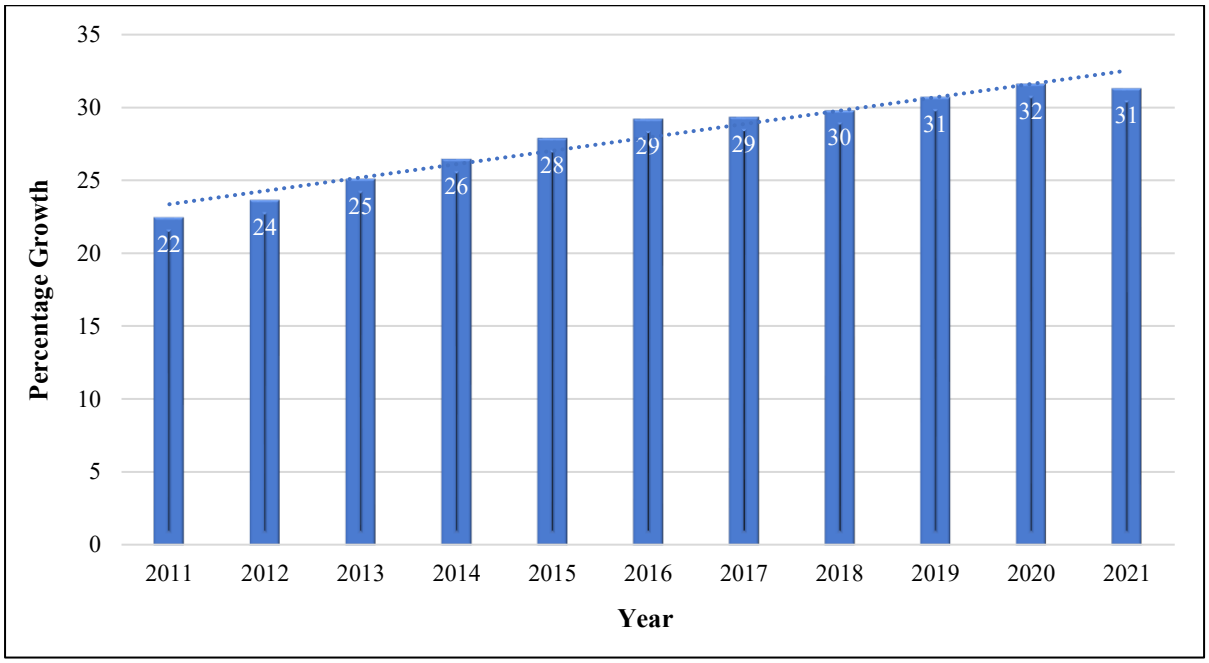
Table 2.12, which follows, indicates the financial inclusion values as per equation (22) for 28 EMDEs with data from 2011 to 2021. It is observed that the United Arab Emirates (UAE) had the highest financial inclusion at 64.3720 in 2021. However, the average financial inclusion for the UAE was slightly lower at 57.6040 due to the lower financial inclusion levels observed in 2011 and 2012. Nonetheless, the financial inclusion levels have been increasing year-on-year. The MENA region offers an opportunity for FinTech due to its youthful, educated and expanding population as well as having some of the highest rates of smartphone, internet and mobile penetration in the world (IMF, 2023).

The UAE is closely followed by Malaysia in terms of financial inclusion levels as according to our findings, Malaysia has a mean inclusion level of 57.4746. Relative to the other countries,

Malaysia's financial inclusion levels were quite high at 57. 6222 in 2011. However, the levels were a bit volatile from 2011 to 2021, hence, the average was 57.4746.

Guinea has the lowest financial inclusion levels according to our study. This country's average financial inclusion level was at 2.1479, based on the data. This comes as no surprise as Guinea suffers from high poverty levels and an informal sector, which makes it challenging for individuals to obtain financial services. This finding also illustrates that barriers are more prevalent in this country. Madagascar, Uganda, and Cameroon also suffer from low financial inclusion levels. Within the 10-year reporting period, these countries' average levels of financial inclusion were 3.4146, 4.9713, and 3.8763, respectively. However, these countries have shown some improvement over the years, albeit at a very small scale.

Figure 2. 4: Average Traditional Financial Inclusion Levels in EMDEs



Source. Calculated by the author

As illustrated by Figure 2.4 above, due to the growing significance of financial inclusion and FinTech in EMDEs in the last decade, there has been an upward trend in the financial inclusion index for EMDEs from 2011 to 2021. Table 2.12 below shows the traditional financial inclusion values for the 28 selected EMDEs. In the analysis, Brazil, Chile, Georgia, Malaysia, and the UAE demonstrated a high level of traditional financial inclusion in the examined time frame, applying the ranking systems developed by Camara and Tuesta (2014).

Table 2. 12: Financial Inclusion values from 2011 – 2021

Country	Year											Mean	Financial Inclusion Level
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021		
Algeria	11.8688	12.1098	13.1458	14.9256	15.9472	15.7075	16.2204	16.6505	17.5254	18.8792	16.0709	15.3683	low
Bangladesh	16.6614	17.0637	17.0253	17.6076	18.3805	16.9275	17.5980	17.9653	18.3044	19.1557	19.5714	17.8419	low
Bolivia (Plurinational State of)	19.0364	20.9268	23.6119	26.5460	29.8456	32.4642	34.6406	35.1694	37.4084	50.3277	51.4209	32.8544	medium
Botswana	22.0638	23.0306	23.2291	23.4900	26.2737	23.7215	23.6370	27.5521	29.1533	29.2710	25.6160	25.1853	low
Brazil	47.3863	51.2112	52.9096	53.4304	53.0532	55.9608	54.6546	54.4919	56.5587	57.6584	57.6579	54.0885	high
Cameroon	2.6615	2.6941	3.0566	3.1435	4.0312	4.2211	4.2895	4.7890	4.7163	5.1606	3.8763	3.8763	low
Chile	53.0360	55.3675	55.7183	55.0317	55.4311	55.5583	54.8878	55.2613	56.3638	56.9656	56.1385	55.4327	high
Colombia	27.7543	29.9446	31.9979	33.5017	35.3698	35.9339	36.3392	36.6458	37.5925	39.2624	36.8492	34.6537	medium
Costa Rica	36.8816	37.6846	41.7983	44.1114	41.3184	43.2517	44.0765	46.8445	46.4463	45.7251	45.4105	43.0499	medium
Dominican Republic	19.6475	19.1285	20.8083	21.2777	23.0928	23.8911	24.0283	23.6112	24.8911	24.9159	24.1197	22.6738	low
Ecuador	22.0956	21.0840	20.8118	22.4853	22.5183	22.9634	23.0208	23.9265	24.8592	25.3922	26.8500	23.2734	low
Egypt	15.0299	14.2934	15.5352	16.8854	18.6162	23.7697	23.6830	23.4527	23.3969	25.7513	28.7528	20.8333	low
Georgia	35.4026	41.4273	47.3785	51.4942	51.8840	56.0027	60.3165	63.2932	63.5230	66.9619	66.9463	54.9664	high
Ghana	7.6998	8.7718	8.3487	8.9322	10.9855	10.9564	11.8894	11.7140	11.9761	11.5169	13.4207	10.5647	low
Guatemala	32.3050	34.1677	35.5991	36.8855	37.4673	37.2148	36.3442	33.0829	32.1498	33.1514	32.2819	34.6045	medium
Guinea	0.1994	0.3133	1.5151	2.3806	2.7978	2.5892	2.4642	2.5374	2.8239	3.0664	2.9393	2.1479	low
Honduras	25.5759	27.2564	28.5006	28.8587	28.3044	29.0165	29.2309	30.1856	30.7494	31.9429	31.4543	29.1887	low
Kenya	12.1950	12.5745	15.3260	18.9410	21.4824	22.9694	22.8277	23.9793	24.0794	27.2955	22.5697	20.3854	low
Lesotho	8.3839	8.5886	9.7948	9.9409	9.9541	10.1691	11.2289	11.4513	11.2282	11.5504	11.8770	10.3788	low
Madagascar	1.7394	1.8758	2.0297	2.4178	2.9707	3.0808	3.5269	4.4532	4.4686	5.1783	5.8188	3.4146	low
Malaysia	57.6222	59.0042	60.4499	59.9777	58.4777	56.6790	55.0382	55.2105	55.8731	57.6664	56.2218	57.4746	high
Namibia	31.1442	31.3686	34.6581	36.3572	37.5134	56.5198	49.3330	47.7432	59.2160	45.2259	44.6699	43.0681	medium
Paraguay	14.3573	16.4074	18.0366	21.2049	22.6876	22.3359	25.3127	27.2757	28.1220	28.0418	28.1498	22.9029	low
Peru	20.5673	22.9339	25.0480	29.2838	43.7342	41.2306	40.4673	42.0132	45.9641	49.7174	48.0490	37.1826	medium
Saudi Arabia	29.4941	29.9656	32.4838	34.8409	38.5541	39.8306	39.5758	37.3463	37.0575	37.6161	38.6092	35.9431	medium
Uganda	3.1537	3.5685	3.7717	3.9415	4.3134	4.5500	4.9661	6.2216	6.7782	6.8813	6.5385	4.9713	low
United Arab Emirates	49.1119	49.6462	50.5959	53.6772	59.5962	63.0061	61.3787	60.1010	59.7441	62.4150	64.3720	57.6040	high
Zimbabwe	5.6415	9.3352	9.4723	9.2254	6.1832	7.1113	10.2159	10.8431	8.5460	7.6953	9.7887	8.5507	low

Source. Calculated by the author using Stata 18

2.14 Panel Estimation Methods and Results

Table 2. 13: Panel Methods Results

	Model			
Variables	**Pooled OLS**	**Fixed Effects**	**Random Effects**	**System-GMM**
lnTFI (-1)				0.7940***(0.0542)
lnFinTech	0.1292***(0.0727)	0.5596***(0.0706)	0.5237***(0.0658)	0.1773**(0.0874)
lnTO	-0.0753 (0.0670)	-0.3632***(0.096)	-0.2985***(0.086)	-0.0679 (0.1271)
lnGOVEXP	-0.0556 (0.0754)	-0.1776 (0.1261)	-0.1329 (0.1107)	0.0472 (0.0711)
lnGNI	0.4307***(0.045)	0.3135***(0.0805)	0.3277***(0.0619)	-0.0917 (0.1115)
lnBM	0.8342***(0.073)	0.6642***(0.1152)	0.6936***(0.1019)	0.2761**(0.1214)
INF	0.0009 (0.0008)	0.0001 (0.0004)	0.0002 (0.0004)	-0.0003**(0.0001)
Intercept	-7.7752***(0.4628)	-4.278*** (0.9949)	-4.9261***(0.7636)	-0.2931 (1.0625)
		Diagnostics		
R-squared	0.7394			
Autocorrelation- Arrelano-				
Bond test (AR 1)				-1.77 [0.076]
Bond test (AR2)				-1.43 [0.153]
Sargan test of overidentifying restrictions				3.29 [0.349]
Hansen test of overidentifying restrictions				1.82 [0.612]
Friedman test of cross-sectional independence		32.442 [0.2161]	32.110 [0.2280]	
No.of Obervations				280
No.of Groups				28
No.of instruments				11

F-Test	24.52 [0.000]	
sigma_u	0.5144	0.5002
sigma_e	0.2132	0.2132
rho	0.8533	0.8462

TFI: Traditional Financial Inclusion ;FinTech: Financial Technology; TO: Trade Openness (% GDP); GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); MS: Broad Money to GDP (Money Supply); INF: Inflation.

Note: Financial inclusion is the dependent variable

Number of observations is 208

****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*

() denote the robust standard errors

[] denote the probability values

Source: Calculated by the author in Stata 18

Table 2.13 illustrates the results of the various panel methods employed by the study. Although the GMM system is our main estimation technique in this study, we estimated a few other model specifications for completeness. There are six explanatory variables in the various estimation techniques – financial technology, trade openness (%GDP), general government final consumption expenditure (% of GDP), GNI per capita (constant 2015 US$), broad Money to GDP (Money Supply), and inflation. Table 2.10 further shows that of the six explanatory variables, three of these (that is, financial technology, inflation, and broad Money to GDP) are significant. The explanatory variables vary in the degree of impact as indicated by the coefficient values.

2.14.1 Pooled OLS results

Based on the Pooled OLS results in Table 2.10, FinTech, broad money to GDP, and GNI per capita are significant at 10%,1%, and 1% significance levels, respectively, while the rest of the variables are insignificant. However, the apparent shortcoming in the Pooled OLS estimation result is the underestimation of the potential significance of heterogeneity among countries.

The fixed effects estimates will inevitably be impacted by the Nickell bias, which could be rather severe, given that the study uses a dynamic panel. Nickell bias is a particular kind of downward bias which impacts the estimated coefficient of the lagged dependent variable, which underestimates its impact on the current results (Nickell, 1981). The lagged dependent variable had a positive correlation with the error in the original OLS regression, which caused its coefficient to be skewed higher and insignificant. This confirms the downward bias with the fixed effects model.

2.14.2 GMM Estimation Technique Results

Among all the estimators, the system GMM estimation technique was the basis for the interpretation of the study results. This is because the system-GMM estimation technique provides the best outcome among the estimators. It is an efficient outcome since additional orthogonality restrictions provided by system-GMM increase efficiency and more dependable instruments are accessible. This study employed the xtabond2 as suggested by Roodman (2009).

a) *Findings on the Main Explanatory Variable (FinTech)*

The main explanatory variable (FinTech) is significant under the system-GMM estimation technique. The results show that, on the main independent variable, FinTech has a significant positive effect on financial inclusion in EMDEs at a 5% significance level. The sign and magnitude indicate that when FinTech increases by a percentage point, the financial inclusion index will increase by a small magnitude of 0.17773 units. This suggests that when individuals accept and adopt FinTech, they will have access to financial products and services, thus, they will be included in the financial landscape. There is hope and aspiration that recent innovations in financial technology (FinTech) will offer unprecedented opportunities to overcome barriers to financial inclusion and close the remaining gaps in ownership and use of bank accounts (or accounts at a financial institution), by taking advantage of the increasing penetration of mobile technology (AFI 2018).

Increasingly, FinTech is a financial inclusion enabler, and mobile financial services are the type of FinTech with the greatest potential to bring the remaining under-banked into the formal financial system and, ultimately, to achieve more equitable growth (GPFI 2016; Demirgüç-Kunt et al. 2018). These results are consistent with findings from Fanta and Makina (2019), and Khalaf and Wadi (2023), who also established a positive relationship between FinTech and financial inclusion in their respective studies.

b) *Findings on Inflation as a Control Variable*

Inflation as a control variable significantly and negatively affects financial inclusion in EMDEs. In other words, there is an inverse relationship between inflation and financial inclusion. For a percentage point increase in inflation, financial inclusion will decrease by 0.0003. The negative relationship between financial inclusion and inflation is aligned with findings from Omar and Inaba (2020), who established that countries with high inflation fluctuations have low levels of financial inclusion, as deposits lose value in the financial sector. The level of inflation has a detrimental influence on the income of poor people, which changes over time. Less income means that households would not be able to access financial services. Ndoricimpa (2017) argues that low levels of inflation enhance growth, and high levels are detrimental to economic growth, especially in low- and middle-income countries. A low level of inflation is therefore expected to improve the level of financial inclusion due to its ability to increase the households' disposable income.

c) *Findings on Broad money to GDP*

Broad money to GDP was found to be positively significant to financial inclusion in EMDEs at a 5% significance level. The sign and magnitude suggest that a percentage point increase in broad money to GDP leads to an increase in financial inclusion by 0.2761 units. Broad money to GDP has an impact on financial inclusion as it affects the cost of financial services and products. For instance, when there is an increase in money supply, this typically results in a decrease in interest rates and financial services fees, thus making it possible for more people to access financial services and products. Moreover, lower costs can also encourage investment in the economy, which could potentially result in more jobs being created. This finding is in line with the assumption that money supply is directly related to economic activities due to its impact on interest rates and the cost of borrowing. Empirically, David, Oluseyi, and Emmanuel (2018) established that an increase in broad money to GDP improves financial inclusion.

d) *Findings on Other Variables*

The rest of the control variables, Trade (% of GDP), government expenditure (% of GDP), and GNI per capita, were, however, found to be insignificant in the model. The findings indicate that these variables do not affect financial inclusion in EMDEs. The serial correlation test, Friedman's test of cross-sectional dependence, and the Sargan and Hansen tests of overidentifying restrictions were used to gauge the model's goodness of fit. These tests support, respectively, the equipment's appropriateness and the errors' sequential correlation. These tests' *p*-values show that the instruments are valid and reliable, with the error terms not serially connected.

The R-squared is 74%, indicating that the variables in the model can explain most of the changes in financial inclusion. We ran additional diagnostic tests on the selected model of the study. To address the potential issues of autocorrelation and heteroskedasticity, we employed the robust form of xtabond2 as proposed by Roodman (2009), which suggests that the test is robust and effective in mitigating autocorrelation and heteroskedasticity in panel data. The autocorrelation results indicate no second-order serial correlations. Thus, the null hypothesis of no autocorrelation could not be rejected since *p* is greater than 0.05. Sargan test of overidentifying restrictions indicates a high *p*-value; as such, we fail to reject the null hypothesis and conclude that there are no overidentifying restrictions. Since the *p*-values of

Friedman's test of cross-sectional dependence tests are greater than 0.05, there is no cross-sectional dependence in the random effect and fixed effect panel models.

The System GMM estimation was performed on a balanced panel of 28 countries using a total of 11 instruments. The GMM-style instruments were constructed using one lag of the endogenous and predetermined variables (L.InFII, L.lnGNI, L.lnTO), and the instrument matrix was collapsed to prevent overfitting while maintaining the orthogonality conditions. This specification is strongly validated by post-estimation diagnostics, particularly the Hansen J-test ($p = 0.612$), which confirms the validity of the instrument set, and the Arellano-Bond test for AR(2) ($p = 0.153$), which supports the absence of second-order serial correlation in the residuals.

2.15 Methodology for Factors Impacting Barriers to Financial Inclusion

This section describes the data that was used and from where it was obtained. It also provides an overview of the variables and techniques employed for the analyses of the study. This section is divided into four parts: data selection and sources, model specification, measurement of the model, and estimation techniques.

2.15.1 Model Specification and Data Sources

The study used secondary data for the analysis. Data for barriers are published every three years by the Global Findex of the World Bank. As such, cross-sectional data was employed, as the year 2021 was chosen arbitrarily for the analysis. Data from WDI and the FAS were also incorporated. The study starts by using the Principal Component Analysis (PCA) approach to reduce the dimensions of the data. The OLS approach was then employed as the main technique.

2.15.2 Description and Measurement of Variables

The following dimensions and indicators were used to measure the factors that impact barriers to financial inclusion in EMDEs.

a) *Barriers (Quality)*

Globally, around 1.4 billion adults were unbanked in 2021. According to the World Bank (2021), developing economies account for nearly all unbanked adults. Unbanked people's perceptions of financial inclusion provide information about the barriers that prevent them from using formal financial services, thus speaking to the quality of financial inclusion. This information is important as it adds to the understanding of financial inclusion by revealing the number of people who are financially excluded as well as the reasons for their exclusion from the formal financial system from their perspective (Camara & Tuesta, 2014). This study considers distance, affordability, documentation and trust as indicators for the barriers dimension. These barriers to financial inclusion have been cited by Demirgüç-Kunt et al. (2021) as the most pertinent involuntary exclusion barriers to consider. For the dimension of the barrier, cross-sectional data from the Global Findex was employed as the data is compiled and published every 3 years. The year 2021 was therefore chosen arbitrarily to examine the relationship between financial inclusion and FinTech in EMDEs.

b) *Explanatory Variables*

This study employed education, GNI per capita, population growth, broad money to GDP, age dependency ratio, and domestic credit provided to the private sector as explanatory variables. However, only credit provided to the private sector is discussed in this section, as the other variables have been explained under the first hypothesis above.

c) *Gross National Income (GNI) per capita*

Gross National Income (GNI) per capita is a metric used to determine the average income of a population of a country. The GNI per capita is a helpful indicator of the development of a country's economy. A positive result is expected because EMDEs already have existing financial institutions in place, which people use to access financial services and products. Chima et al. (2021) and Menyelim et al. (2021) used GNI per capita as a control variable in their respective studies.

d) *Education*

The gross enrolment ratio in primary education is used as a measure to determine the proportion of children who are of primary school age and are enrolled in primary school as a proportion of the corresponding age group (World Bank, 2022). Due to the inherent complexity of

financial products, education emerges as a critical determinant affecting households' decisions to use or refrain from using financial services. Therefore, education is vital in promoting financial inclusion (Fagerlind & Saha, 1989; Mzobe, 2015). Therefore, a positive outcome was expected. Demir et al. (2022) employed education as one of the control variables in their study.

e) *Age Dependency ratio*

The World Bank (2020) defines the age dependency ratio as a measurement of the proportion of dependents (both children and elderly individuals) to the working age group (from 15 to 64 years). A country's economy can be strained if many people cannot work due to age restrictions. This is because people who qualify to work would have to support the people who cannot work because of their age through taxes and other government programs. Most developing countries have high unemployment; therefore, a negative outcome is expected between barriers to financial inclusion factors and the age dependency ratio. This variable was also employed in a study by Neaime and Gaysset (2018).

f) *Domestic Credit Provided to the Private Sector*

Credit provided to the private sector refers to financial products offered by the depository corporations to the private sector; these financial products include purchases of nonequity securities, loans, trade credits, and other accounts receivable (WDI, 2022). Nsiah and Tweneboah (2023) employed credit provided to the private sector as one of the explanatory variables in their study.

Table 2. 14: Summary of the Explanatory Variables' Aprior signs

Variable	Description	Expectation Indication	Data Source
EDU	Education	Positive (+)	WDI
GNI	GNI per capita	Positive (+)	WDI
BM	Broad Money to GDP	Positive (+)	WDI
DPR	Dependency Ratio	Negative (-)	WDI
DCPS	Credit Provided to the Private Sector	Positive (+)	WDI

Source: Author's expectations

2.15.3 Unit Root Test

Before beginning the estimation process, this study uses the latest and most effective panel unit roots and cointegration approaches to examine the stationarity of the data. This study proposes the IPS (Im et al., 2003) test.

The IPS test is regarded as a first-generation test that is suitable when cross-sectional units are independent of one another (Westerlund & Breitung, 2013). The application of the augmented Dickey-Fuller (ADF) test to the panel serves as the foundation for the IPS test (Christopoulos & León-Ledesma, 2007). The main purpose of the IPS test is to determine whether variables are stationary or not (Yüksel, 2017). The IPS test has a null hypothesis that a unit root exists in every panel (Rusike, 2020), while the alternative hypothesis states that all single series are stationary (Mehrara et al., 2011).

2.15.4 Principal Component Analysis

This section outlines the methodology for constructing a barrier index (BARi) using PCA, mirroring the procedures established for financial inclusion and FinTech indices. The following equation was used:

$$BAR_{i} = w_1 DIS_i + w_2 TRU_i + w_3 AFF_i + w_4 DOC_i + e_i \quad (23)$$

where; BAR_i is the index for the i^{th} year and W_1, W_2,…,W_3 are the respective weights of different variables. DIS, TRU, AFF, and DOC denote distance, trust, affordability, and documentation. Equations (4) to (11) under the first hypothesis are followed and repeated using barrier indicators to construct an index.

2.5.6 Estimation Technique

The OLS technique has been explained in detail under the first hypothesis. The OLS model is illustrated below:

$$BAR_i = \alpha_0 + \alpha_1 EDU_i + \alpha_2 GNI_i + \alpha_3 BM_i + \alpha_4 DPR_i + \alpha_5 DCPS_i + \varepsilon_1 \quad (24)$$

where; BAR_i represents the barriers index, EDU_i denotes education, GNI_i is the GNI per capita, BM_i is the broad money to GDP, DPR_i is the dependency ratio, $DCPS_i$ domestic credit to

private sector by banks (% of GDP), and, α is the coefficient of the estimated equation. The analysis is performed using EViews 13 and Stata 17 statistical software packages.

2.16 Empirical Results and Discussion

This section addresses data analysis and interpretation of all variables estimated in this study and is further divided into five subsections. The results of the PCA used to build the financial inclusion index are explained first. Next are the descriptive statistics, as well as various diagnostic tests that were used, followed by analyses of the results of the OLS used to investigate the factors that impact barriers to financial inclusion in EMDEs. The last segment discusses the results of whether barriers to financial inclusion affect the quality of financial inclusion or not.

2.16.1 Descriptive Statistics

Table 2.15 below depicts the descriptive statistics of the variables used to examine the factors that impact barriers to financial inclusion in EMDEs.

Table 2. 15: Summary Statistics on Factors that Impact Barriers to Financial Inclusion

Variables	Observations	Mean	Standard deviation	Minimum	Maximum
BARR	28	0.7853	0.4496	0.1112	1.9942
EDU	28	106.0798	13.1257	70.0000	143.2202
GNI	28	6419.5900	8073.9850	439.6943	40730.5700
BM	28	59.5320	29.8437	14.9019	133.1787
DPR	28	57.7705	15.1180	20.3390	88.2134
DCPS	28	44.2308	27.5200	6.9263	127.5061

BARR: Barrier; EDU: Gross enrolment ratio in primary education; GNI: Gross National Income per capita; BM: Broad Money to GDP; DPR: Age Dependency Ratio; DCPS: Credit Provided to the Private Sector

Source. Calculated by the author using Stata 18

Table 2.15 above depicts the descriptive statistics of the variables used to investigate the factors that impact financial inclusion barriers in EMDEs. The average level of barriers to financial inclusion in the selected EMDEs from 2011 to 2021 was relatively high, reaching 0.7853 with a standard deviation of 0.4496. This demonstrates that there are significant barriers to financial inclusion in the selected EMDEs, and the level of barriers varies considerably. Education has a mean of 106.0798 and a standard deviation of 13.1257. The average Gross National Income (GNI) per capita is $6419.59 with a standard deviation of $8073.9850, thus demonstrating

notable deviations in the GNI per capita of the selected EMDEs. Broad money to GDP recorded a mean value of 59.5320 and a standard deviation of 29.8437, illustrating a money supply system that is reasonably stable. The dependency ratio averaged 57.7705 with a standard deviation of 15.1180, suggesting that the ratio of dependent individuals to working-age individuals remained stable. The average domestic credit to the private sector (% GDP) was recorded at 44.2308 with a standard deviation of 27.5200, thus illustrating a stable variable.

2.16.2 Unit Root Test Results

The study employed the Im et al. (2003) unit root test. The results are shown in Table 2.16, which follows.

Table 2. 16: Unit Root Test Results for Barriers Dataset

Variable	Im, Pesaran, and Shin	
	Level	
	Constant	Constant +Trend
BARR	-3.7648***	-3.6888**
	(0.0086)	(0.0407)
EDU	-7.8314***	-7.6703***
	(0.0000)	(0.0000)
GNI	-3.335**	-3.4419*
	(0.0231)	(0.0668)
BM	-4.2536***	-4.7293***
	(0.0026)	(0.0041)
DPR	-3.0764**	-4.277**
	(0.0405)	(0.0115)
DCPS	-5.019***	-6.7152***
	(0.0004)	(0.000)

Note: () denote the p-values
****, **, denote the significance at the 1% and 5% levels, respectively*

Source: Calculated by the author in Stata 18

The LLC test was performed to assess whether each variable in the study had a unit root or not. The outcome of the IPS test from this study shows that all variables are stationary at the level, therefore, we reject H_0.

2.16.3 Multicollinearity – Variance Inflation Factor

The VIF was employed to test for multicollinearity. The results show that the VIFs of the independent variables as per Table 2.17, which follows, are less than 10, indicating no multicollinearity.

Table 2. 17: Variance Inflation Factor Test

Variables	VIF	1/VIF
EDU	1.03	0.9714
GNI	2.39	0.418129
BM	3.65	0.273794
DPR	3.94	0.254079
DCPS	3.96	0.252304
Mean VIF	**2.99**	

Source. Calculated by the author using Stata 18

2.16.4 Pairwise Correlation Matrix for Cross-Sectional Data

This section discusses the correlation that exists between the dependent variable (barriers) and each of the explanatory variables. The pairwise correlation matrix is presented in Table 2.18 below.

Table 2. 18: Pairwise Correlation Matrix for Cross-Sectional Data

	BARR	EDU	GNI	BM	DPR	DCPS
BARR	1					
EDU	0.217	1				
GNI	-0.5439	0.065	1			
BM	-0.5937	0.0846	0.47	1		
DPR	0.5444	-0.0984	-0.7568	-0.6891	1	
DCPS	-0.5094	0.0134	0.4738	0.8405	-0.7131	1

BARR: Barriers; EDU: Education;); GNI: GNI per capita (constant 2015 US$); BM: Broad Money to GDP (Money Supply); DPR: Age dependency ratio; DCPS: domestic credit to private sector

Source. Calculated by the author using Stata 18

None of the selected variables have a correlation coefficient of greater than 0.8, thus indicating that there is no multicollinearity between the variables. Education is positively correlated with barriers to financial inclusion. The correlation coefficient of 0.2 indicates a weak positive relationship between education and barriers. GNI per capita is negatively correlated to barriers

to financial inclusion with a moderate correlation coefficient of 0.5. Like GNI per capita, broad money to GDP is also negatively correlated to barriers to financial inclusion with a moderate correlation coefficient of 0.5. The age dependency ratio positively correlated with barriers to financial inclusion. The correlation coefficient of 0.5 indicates a moderate positive relationship between the age dependency ratio and barriers to financial inclusion. Domestic credit to the private sector is negatively correlated with barriers to financial inclusion. The correlation coefficient of -0.5 between these two variables indicates that there exists a moderate correlation.

2.16.5 Estimated Results for Barriers Index

PCA can be performed if KMO>=0.5 and X^2 (Chi-square) in Bartlett's test of sphericity is statistically significant. As illustrated in Table 2.19, the KMO test for this study is 0.632, which indicates that the data used for this study is suitable and appropriate. Bartlett's test of sphericity has an X^2 of 122.110 and a *p*-value of 0.000, which shows that there is no correlation between the selected indicators of the study.

Table 2. 19: Kaiser–Meyer–Olkin Measure and Bartlett's Test of Sphericity

Test	Measure	Barriers' dataset
Kaiser–Meyer–Olkin		0.632
Bartlett's test of sphericity	Chi-square	122.110
	Degrees of freedom	21
	p-value	0.000

Source. Calculated by the author using Stata 18

Using STATA 18, a measuring model for constructing a financial inclusion index was carried out. The barriers dimension was used in the measurement model.

Table 2. 20: Principal Components Estimates for Sub-Indices

Variable	Eigenvalue	Difference	Proportion	Cumulative
Barriers dimension				
Comp1 (Distance)	3.4989	3.1810	0.8747	0.8747
Comp2 (Affordability)	0.3179	0.2125	0.0795	0.9542
Comp3 (Documents)	0.1054	0.0276	0.0263	0.9806
Comp4 (Trust)	0.0778	0	0.0194	1

Source. Calculated by the author using Stata 18

The results of the first-stage PCA are illustrated in Table 2.20 above. The eigenvalues of each sub-index and latent variables are determined by using the PCA method. Principal components with eigenvalues greater than one are the only ones considered for the analysis, as the component with the highest eigenvalue retains more standardised variance relative to the rest (Kaiser, 1960; Nguyen, 2020). As per Table 2.14, the eigenvalues of the principal components for the dimension of the barrier are as follows: 3.4989, 0.3179, 0.1054, and 0.0778. None of the other principal components have an eigenvalue greater than one, apart from the first principal (component 1 of the access and usage dimensions). As a result, only the first component was used for the analysis, while the estimations of the dimensions were done using weights allocated to the first component of each dimension.

Table 2. 21: Scoring Coefficients for Orthogonal Varimax Rotation (Weights)

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Unexplained
Barriers dimension					
Distance	0.5107	0.2355	-0.7773	-0.2822	0
Affordability	0.4937	-0.6057	-0.0836	0.6183	0
Documents	0.4841	0.6947	0.4021	0.3483	0
Trust	0.5109	-0.3083	0.4766	-0.6455	0

Source. Calculated by the author using Stata 18

The retrieved weights of each of the four indicators are displayed in Table 2.21 above. Considering this, for the dimension of the barrier, the weight assigned for the first component is 0.5107 for the *distance* indicator; 0.4937 for the *affordability* indicator, 0.4841 for the *documents'* indicator, and 0.5109 for the *trust* indicator.

The weights of the respective indicators are allocated in equations (13) as follows:

$$\mathrm{BAR}_i = 0.5107DIS_i + 0.5109TRU_i + 0.4937AFF_i + 0.4841DOC_i + \boldsymbol{e}_i \quad (25)$$

2.16.6 Estimation Results of Pooled OLS

Table 2. 22: OLS Estimation Results

Dependent Variable: BAR (2021Y)	
Variable	**Pooled OLS**
EDU	0.0098*
	(0.0040)
GNI	-0.000019*
	(0.0000)
BM	-0.0081**
	(0.0034)
DPR	0.0007
	(0.0068)
DCPS	0.0020
	(0.0040)
Intercept	0.2240
	(0.9603)
Diagnostics	
R-squared	0.5233
F-statistic	5.75
Prob(F-statistic)	0.0015
Shapiro–Wilk W test for normal data	-0.681[0.7521]
Heteroskedasticity	1.36 [0.2431]

Note: Barriers are the dependent variable
The number of observations is 28
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*
[] denotes the probability values
() denotes the robust standard errors

Source: Calculated by the author in Stata 18

The OLS results in Table 2.22 reveal that three out of the five explanatory variables are significant to the dependent variables. These results are discussed in more detail below.

The study found that education has a positive and significant impact on barriers to financial inclusion at a 10% significance level. The size and sign demonstrate that a percentage point increase in education will lead to a small increase of 0.0098 in factors that impact barriers to financial inclusion in EMDEs. Educated individuals are more likely to have access to financial products and services and make use of these products as they can understand the various products offered, therefore, they can make well-informed decisions. This result is supported by

existing literature (Sanderson et al., 2018; Dar & Ahmed, 2021). A study by Chikalipah (2017) also established that illiteracy is a major barrier to financial inclusion.

a) *Findings on GNI per capita*

The GNI per capita has a negative and significant impact on barriers to financial inclusion at a 10% significance level. The size and sign demonstrate that a one-dollar rise in per capita income will result in a small decrease of 0.00001278 in the barriers to financial inclusion in EMDEs. This implies that households are encouraged and enabled to overcome financial inclusion barriers as their income increases. Hence, an increase in household income makes it easier for households to afford and have access to more essential financial services and products. Furthermore, households will be more willing to use financial services and products provided by banks because of their trust in them. Affordability and trust are some of the barriers evaluated in this study, therefore, an increase in household income will assist in alleviating the magnitude of these barriers, thus, resulting in increased financial inclusion. This is consistent with a study by Nsiah and Tweneboah (2023) who found that households and firms are empowered to overcome barriers as their income increases.

b) *Findings on Broad money to GDP*

Broad money to GDP was found to negatively and significantly impact the barriers to financial inclusion at a 5% significance level. The size and sign imply that a percentage point increase in broad money to GDP results in a 0.0110 decrease in barriers to financial inclusion in EMDEs. When broad money to GDP increases, financial institutions, such as banks, have more money to lend out. Ultimately, this makes it easier for households to have access to essential financial services and products. This finding is consistent with a study by David et al. (2018). The age dependency ratio and domestic credit to private sector variables were the only non-significant variables. This suggests that these variables do not have any impact on eradicating barriers to financial inclusion in Africa.

The R-squared is 52%, indicating that the variables in the model can explain most of the factors that impact barriers to financial inclusion in EMDEs. Additional diagnostic tests were conducted on the OLS model. The Shapiro–Wilk W test was used to test for normality, and the results reveal that the data is normally distributed, therefore, the null hypothesis could not be rejected. The conducted heteroskedasticity tests yielded a result wherein the null hypothesis,

positing homoscedasticity (constant variance of errors), could not be rejected. In addressing the presence of heteroskedasticity, this study employed the robust specification of xtabonds2, as recommended by Roodman (2009), thereby enhancing the validity of the panel data analysis.

2.17 Concluding Remarks

The study set out to estimate the impact of FinTech on financial inclusion in 28 EMDEs and employed panel techniques. Factors impacting barriers to financial inclusion in these countries were assessed using the OLS technique. This study has discussed the theoretical underpinnings of the relationship between FinTech and financial inclusion in EMDEs through the lens of the Technology Acceptance Model developed by Davis (1989). However, we found that to better understand the rapid changes in innovation in different parts of the world, the Diffusion of Innovation theory by Rogers (1962) would also be appropriate.

The extant literature illustrates that in most regions, FinTech increases financial inclusion. For instance, FinTech innovations have been produced and adopted in the Africa, Asia, and Middle East regions. Previous research indicates that FinTech can effectively promote financial inclusion, particularly in EMDEs. FinTech has been instrumental in improving financial inclusion in these regions. Nonetheless, there are conflicting findings on the relationship between FinTech and financial inclusion in the LAC region. Some empirical evidence suggests that FinTech is still in its early stages and has little effect on financial inclusion in the region. On the other hand, some studies show that FinTech has a positive effect on financial inclusion in the region. The broad agreement is that FinTech promotes financial inclusion in EMDEs.

This study constructed a new multidimensional financial inclusion index for 28 EMDEs using weights derived from the PCA in aggregating indicators for two dimensions: access and usage, following Camara and Tuesta (2014). The index can be used to compare the extent of financial inclusion across different EMDEs and to monitor their progress over time. The countries with the highest level of financial inclusion were the UAE, Georgia, and Brazil. Conversely, Guinea, Madagascar, Cameroon, Uganda, and Zimbabwe exhibited some of the lowest financial inclusion levels. Therefore, governments and policymakers in these and other EMDEs with low levels of financial inclusion should develop suitable financial inclusion initiatives, make investments in effective and affordable digital payment systems, and promote the creation of financial services and products that are innovative affordable, and adapted to the needs of the financially excluded individuals.

A new FinTech index was also constructed for 28 EMDEs by using variables such as individuals using the Internet (% of the population), mobile cellular subscriptions (per 100 people), and fixed broadband subscriptions (per 100 people) (Emara & Mohieldin, 2021; Kouladoum et al., 2022). Weights derived from PCA were used for the construction of the index. Additionally, a new barriers index was developed using distance, trust, affordability, and documentation as variables. Similarly, weights derived from PCA using Stata 17 were employed for the construction of the index. Moreover, a new barriers index was developed using distance, trust, affordability, and documentation as variables. Similarly, weights derived from PCA using Stata 18 were employed for the construction of the index.

The main objective of this study was to assess the impact of FinTech on financial inclusion in EMDEs using dynamic panel techniques. The study provided a simultaneous cross-country analysis from the selected regions and employed various estimation techniques for completeness. These techniques included OLS, fixed effects, random effects, and system-GMM. Upon running the various estimation techniques, it was established that the main explanatory variable (FinTech) was only significant under the system-GMM technique, thus making it the most appropriate technique for the study. The estimates provided robust evidence that illustrated that FinTech has a positive and significant impact on financial inclusion in EMDEs.

Some control variables were significant to the dependent variable (financial inclusion). These control variables included the broad money to GDP and inflation. However, Trade (% of GDP), government expenditure (% of GDP), and education were found to be insignificant to financial inclusion. Governments and policymakers should consider developing frameworks that support FinTech development that are appropriate and responsible while considering risks and customer protection. Access to inexpensive mobile connectivity and internet should be increased, particularly in underserved regions.

The study further examined the factors that impact barriers to financial inclusion in EMDEs. The study found that education, GNI per capita, and broad money to GDP affect barriers to financial inclusion in EMDEs. The age dependency ratio and domestic credit to private sector variables did not impact barriers to financial inclusion in EMDEs. Policymakers should consider funding financial literacy and high-quality education initiatives with a focus on EMDEs. Further, policymakers should prioritise decreasing poverty and increasing sustainable jobs while also implementing inclusive economic growth strategies.

The financial inclusion levels observed in the 28 sampled EMDEs significantly vary year-on-year. There are currently 1.4 billion adults who are unbanked in EMDEs (World Bank, 2021). Nonetheless, there is a disparity in the level of financial inclusion amongst the sampled EMDEs. It was observed that some countries have reached high levels of financial inclusion while others still have very low financial inclusion levels. For instance, of the 28 sampled EMDEs, five (5) countries had high levels of financial inclusion, seven (7) had medium levels of financial inclusion, and 16 had low levels of financial inclusion. EMDEs should make efforts to promote FinTech and improve financial inclusion in their countries.

CHAPTER 3

THE EFFECT OF INSTITUTIONAL QUALITY ON DIGITAL FINANCIAL INCLUSION IN EMERGING AND DEVELOPING ECONOMIES

3.1 Introduction

Many developing countries tried to improve financial inclusion after the 2007/8 global financial crisis to promote economic development. Although the necessity of specific development goals remains a central focus in the debate regarding the impact of institutional quality on financial access in developing countries, attention is increasingly directed toward the methods for achieving these goals. When institutional quality is low, people are discouraged from engaging in the legally regulated financial sector, making it one of the key factors determining whether people and companies participate in mainstream financial institutions (Zeqiraj et al., 2022). The Neo-institutional theory explains that institutional quality is important in the financial sector as it can promote a financial environment that is favourable to the expansion and development of financial services.

The performance of financial institutions can be hindered by poor institutional quality, which includes pervasive corruption, substandard corporate governance, lax enforcement of property rights, political turmoil, and unaccountable leadership (Aracil et al., 2022). Moreover, poor institutional quality may increase the risk of financial losses in financial institutions, which may, in turn, discourage people from placing money in well-established financial institutions, thus increasing financial exclusion.

Financial intermediaries' ability to efficiently channel capital to fund productive activities tends to be impacted by weak institutions (Law et al., 2014). Levine (1998) indicates that institutions are crucial for the functioning of financial markets. Therefore, unstable governments cannot commit credibly to implementing policies that can support and encourage innovative and entrepreneurial endeavours. Additionally, institutional instability often leads to weak macroeconomic conditions, which hinders financial inclusion. Therefore, a lack of in-depth knowledge about digital financial inclusion and institutional quality could have disastrous implications for EMDEs.

Although there is currently no consensus on how to define digital financial inclusion, it generally refers to making use of technology to provide financial services and products to individuals who were previously financially excluded (Ozili, 2022). Reliable and effective institutions offer a conducive environment for digital financial services by providing innovation, financial stability, transparency, and secure transactions. As a result, this encourages potential investors and individuals, particularly those previously underserved, to participate in the formal financial sector.

3.2 Perspectives on Institutional Quality

Existing literature emphasises that improving financial inclusion depends in part on the quality of institutions (Kwenda & Chinoda, 2019). However, there are limited studies on the relationship between institutional quality and financial inclusion from a digital perspective (that is, digital financial inclusion) (Doku et al., 2023). Existing literature has mainly considered traditional financial inclusion indicators and dimensions. Moreover, Boukhatem and Moussa (2023) argue that institutional quality has not received much attention in research despite being crucial for promoting financial inclusion. A country's economy is impacted by the quality of its institutions (Aracil et al., 2022). For instance, by continuously striving to improve and strengthen the quality of their institutions, EMDEs can enhance the state of their economies and foster a more inclusive financial system. Therefore, this creates a gap in the literature that needs to be explored.

Furthermore, there is insufficient research on institutional quality and digital financial inclusion from EMDEs' perspective as most studies have focused on specific countries as opposed to a cross-section with several countries. Therefore, there has not been much attention on simultaneously investigating the effect of institutional quality on digital financial inclusion in various EMDEs. In the African region, most of the studies found that institutional quality positively affects financial inclusion (Akintunde & Aribatise, 2022; Chinoda & Kapingura, 2024; Doku et al., 2023; Kwenda & Chinoda, 2019). Similarly, in the Asian region, most studies suggest that institutional quality positively impacts financial inclusion (Hassan et al., 2023; Nasreen et al., 2023). Institutional quality determines whether households and businesses engage in the financial system.

3.3 Contribution of the Study

However, the effect of institutional quality on digital financial inclusion has received limited scholarly attention in the other regions that we focus on in this study, such as Oceania and South-Eastern Europe. Thus, this research contributes to the scarce literature in these regions. In addition, Zeqiraj et al. (2022) contend that there is still a need to conduct further research in this field. Examining a variety of countries simultaneously identifies trends that might not be apparent or too obvious in a single country. This enables more broadly applicable conclusions regarding this chapter's topic. The analytical techniques employed in this chapter sought to establish the effect of institutional quality on digital financial inclusion in EMDEs. Considering the shortcomings, this study adds to the body of knowledge in several ways.

a) *Panel ARDL Analysis of Digital Financial Inclusion*

First, this study empirically examined the short and long-run cointegration between institutional quality and digital financial inclusion in EMDEs by using panel autoregressive distributed lag (ARDL) as the main estimation technique. Using the panel ARDL has several benefits, one of which is that it is more efficient than other cointegration techniques in instances in which the sizes are finite and small (Raji, 2021). The ARDL technique can also handle endogeneity and serial correlation problems amongst variables. The study constructed a new digital financial inclusion index by employing the principal component analysis (PCA) approach. The index enables a cross-country comparison of the level of digital financial inclusion and provides a consistent method for monitoring progress across various countries. Governments and policymakers in the selected countries can use the digital financial inclusion index to identify initiatives and programmes that can help improve their digital financial inclusion levels.

b) *Institutional Quality and the Digital Dimension of Financial Inclusion*

Additionally, contrary to most studies that have examined the relationship between institutional quality and financial inclusion from a traditional standpoint (Aracil et al., 2022; Muriu, 2020; Nguyen & Ha, 2021; Nkoa & Song, 2020), the present study focuses on the effect of institutional quality on financial inclusion from a digital perspective.

c) *Focus on Under-Researched Regions*

Moreover, this study investigated the effect of institutional quality on digital financial inclusion in Central Africa, Southern Africa, West Africa, Oceania, West Asia and South Asia as there is limited research in these regions that investigate the short and long-run cointegration between institutional quality and digital financial inclusion and hence require more consideration.

d) *Leveraging Panel Data for Robust Empirical Results*

Lastly, this study employed panel data as it provides more insightful data, improves efficiency, provides more variability, and reduces variable collinearity (Gujarati, 2003; Greene, 2005; Woolridge, 2002). Panel data provided a way of managing unobserved countries and or time-specific heterogeneity, which could be correlated with the explanatory variables included in the study (Akbar et al., 2011).

e) *Policy Implications: Institutional Quality and Digital Finance*

Investigating the short and long-run effect of institutional quality on digital financial inclusion can be beneficial as comprehending the short- and long-term barriers can assist governments and policymakers in EMDEs in prioritising and implementing suitable initiatives to drive digital financial inclusion in these countries. Findings from the study revealed that institutional quality (the main explanatory variable) has a positive effect on digital financial inclusion in the long run but not in the short run. The sign and magnitude indicate that when institutional quality increases by a percentage point, the digital financial inclusion index will increase by 0.5887. Robust institutions possess the ability to ensure the safety and reliability of digital financial services. Establishing trust is essential in fostering confidence among prospective customers who may exhibit hesitancy towards utilising digital financial services.

3.3.1 Study Overview

This study examined the impact of institutional quality on digital financial inclusion within EMDEs. It begins by establishing a foundational understanding through a review of existing literature and a conceptual analysis, grounding the subsequent investigation in established theoretical and empirical frameworks. The methodology employed is then outlined, followed by a comprehensive data analysis, encompassing descriptive statistics, various estimation

techniques, and a discussion of the findings and their implications. Finally, the study concludes with a summary of the analysis and provides recommendations derived from the research.

3.4 Literature Review

This section delves into the existing literature, first defining the multifaceted concept of digital financial inclusion and then examining the diverse methodologies employed for its measurement. Notably, it highlights the shift from traditional financial inclusion metrics to more nuanced indices that capture the digital dimensions of access and usage.

3.4.1 The Concept of Digital Financial Inclusion

Policymakers and academics are becoming increasingly concerned with the access and usage of financial services and products (Arun & Kamath, 2015). There is currently no unified definition of digital financial inclusion. According to the Consultive Group to Assist the Poor (2015) report, digital financial inclusion entails excluded and underserved populations having digital access to and use of formal financial services. Similarly, Ebong and George (2021) define digital financial inclusion as a broad term that refers to a variety of financial services that can be accessed and delivered through digital media. Payments, credit, savings, remittances, and insurance are examples of financial services. The World Bank (2014) defines digital financial inclusion as the deployment of cost-effective digital means to reach currently financially excluded and underserved populations with a range of formal financial services tailored to their needs that are responsibly delivered at a cost that is affordable to customers and sustainable for providers.

Most people in EMDEs do not have access to traditional financial services and products offered by financial institutions such as banks. By using technology, digital financial services can reach households and firms that have historically been underserved or excluded from conventional financial services. Greater financial inclusion is fostered by these innovative technologies, which make it possible for people to overcome barriers such as high transportation costs, physical infrastructure limitations, and geographic distance (Banik & Roy, 2023).

3.4.2 Measurement of Digital Financial Inclusion

To date, there is no universal method for quantifying how to measure digital financial inclusion. This makes managing digital financial inclusion difficult, especially in EMDEs. Most current

research is mainly focused on traditional financial inclusion, that is, financial inclusion made possible by banks. Traditional financial inclusion is typically measured by access and usage as dimensions and corresponding indicators such as ATMs, bank branches, loans, and deposits. Khera et al. (2022) argue that although existing literature (such as Camara & Tuesta, 2014; Loukoianova et al., 2018) has attempted to measure the level of digital financial inclusion, it has mainly focused on indicators such as mobile money transactions, and money accounts. Further, these indicators only capture one facet of digital financial inclusion at a particular moment in time and fail to provide a holistic picture that incorporates a variety of factors (Khera et al., 2022). Consequently, there have been various attempts and recommendations on how to measure digital financial inclusion.

More recently, some studies have measured digital financial inclusion by focusing on the access and usage dimensions and their corresponding indicators (Ahamed and Mallik, 2019; Khera et al., 2022). For instance, Khera et al. (2022) employed indicators related to access and usage to measure digital financial inclusion in 52 EMDEs in 2014 and 2017. The primary indicators of access are those about the availability of ways to obtain payment services. These are considered supply-side elements. On the other hand, the usage dimension mainly focuses on the demand-side components of digital financial inclusion. Indicators related to digital financial inclusion, such as the number of adults using the internet (% of the population), the number of mobile subscribers per 100 adults, registered mobile money agents per 100,000 adults, and active mobile money accounts per 1000 adults, have increased between 2014 and 2020 (Chinoda & Kapingura, 2024). These dimensions and indicators were then employed to construct a digital financial inclusion index. In a similar study, Banik and Roy (2023) constructed a digital financial inclusion index by using access, usage, and availability as dimensions, together with their respective indicators. Due to data availability, the current study followed Khera et al. (2022) to measure digital financial inclusion.

The digital financial inclusion index has advantages over the traditional financial inclusion index as it does not solely focus on access and usage of financial services through traditional channels of distribution, such as banks. For instance, the digital financial inclusion index offers a deeper comprehension of how digital finance advances financial inclusion.

3.5 Theoretical Review

This section outlines the theoretical underpinnings of the study, beginning with Neo-institutional theory, which posits that institutional quality significantly influences economic participation, including digital financial inclusion. It then briefly introduces the Diffusion of Innovation Theory, setting the stage for subsequent theoretical exploration.

3.5.1 Neo-Institutional Theory

One of the primary theoretical stances utilised to comprehend organisations and broader social forces' behaviour, particularly more general cultural norms and beliefs, is the Neo-institutional theory (Lounsbury & Zhao, 2013). Therefore, the present study is underpinned by the Neo-institutional theory, which states that the effectiveness of an economy's system is contingent upon the quality of institutions operating in it (North, 1990). The institutional framework of a country can be classified as either inclusive or extractive. Extractive political institutions favour a few elite individuals at the expense of most of the population. They are distinguished by the concentration of power to a few individuals and are often not transparent (Robinson & Acemoglu, 2012).

Consequently, many EMDEs view the existence of extractive institutions, which provide the government with the power to seize residents' money, as a significant barrier to their ability to achieve economic success (Mizuno et al., 2017). Acemoğlu and Robinson (2016) argue that for inclusive political institutions to exist, a state must have the resources to function, and political authority must be widely spread throughout society. Put differently, inclusive political institutions develop from an even and fair distribution of power and balance expansion in state capacity. The notion that shifts towards inclusive political institutions is the result of the organisation of a sizeable social coalition that, if it gains power, has the incentive to act on both margins, enhancing state capacity and spreading political power (Acemoğlu & Robinson, 2016).

Financial inclusion is vital and has increased at twice the rate of other crucial institutional dimensions such as education and health (Demirgüç-Kunt et al., 2018). Some scholars define financial inclusion as the process of ensuring that individuals, particularly the poor, have access to essential financial services in the formal financial sector (Allen et al., 2016; Ozili, 2018). Although existing literature does not provide a standard definition for this phenomenon, each

of the different definitions encompasses either access, usage, or availability of financial services. Considerable literature has proven financial inclusion's positive effect on poverty reduction through expanded availability of financial services (Churchill & Marisetty, 2020; Hussaini & Chibuzo, 2018; Mohammed et al., 2017). The lack of strong institutions in a country is reflected in corruption (Collier, 2002). Efforts to reduce financial exclusion can be hampered by extractive institutions, particularly, by high levels of corruption. In contrast, the increase of digital financial inclusion can be enhanced by effective financial institutions.

institutional quality significantly impacts economic growth and poverty eradication (Acemoğlu & Robinson, 2016). Similarly, the quality of financial institutions available in various countries affects digital financial inclusion. The neo-institutional theory is appropriate for this study because it suggests that when the institutional quality of an economy is effective, it encourages individuals to participate in the financial markets, thus increasing digital financial inclusion. The opposite is also true – when institutional quality is not effective in an economy, it often leads to people not taking up in the financial sector. Thus, this study examined the effect of institutional quality on digital financial inclusion in EMDEs.

3.5.2 Diffusion of Innovation Theory

To understand the rapid changes in innovation, this study has further employed the DOI theory. This theory has been explained in detail in Chapter 2. The theory examines the process by which new ideas and technologies spread through a population, detailing the stages of adoption and the factors that influence this spread, such as the innovation's characteristics and social dynamics. It categorises adopters based on their timeline, from innovators to laggards, providing a framework for understanding how acceptance evolves within a society. Ultimately, this theory helps researchers and practitioners analyse and predict the adoption of new technologies and concepts, offering insights into how to effectively promote their dissemination.

3.6 Review of Empirical Literature

Several empirical studies have debated the relationship between financial inclusion and institutional quality for various countries for many years. Institutional quality factors such as voice and accountability, regulatory quality, the rule of law, political stability, government effectiveness, and control of corruption have been employed by most studies. On the other

hand, financial inclusion dimensions and indicators used in the existing literature have mainly been for traditional financial inclusion and not digital financial inclusion. Moreover, the effect of institutional quality on digital financial inclusion, particularly in EMDEs remains under-researched.

3.6.1 Institutional Quality and Digital Financial Inclusion in Asia

Nguyen and Ha (2021) investigated the effect of institutional quality on financial inclusion in the Association of Southeast Asian Nations (ASEAN) using data from 2008 to 2019. The researchers employed a PCA approach to construct a financial inclusion index. Using traditional financial inclusion indicators, three dimensions (penetration, availability, and usage) were employed. For the penetration dimension, ATMs per 1000 km^2 and the number of bank branches per 1000 km^2 were used. The number of ATMs per 10,000 and the number of bank branches per 100,000 were considered for the availability dimension. For the usage dimension, the ratio of credit to private to GDP and the ratio of deposit to private to GDP were used as proxies. For institutional quality, six indicators were employed. For robustness, the study further employed a Generalized GMM for regression analysis purposes. The study found that there was a positive impact of institutional quality on financial inclusion.

Using a sample of 23 Asian countries from 2006 to 2017, Hassan et al. (2023) evaluated the impact of financial inclusion and institutional quality on economic growth. Static and dynamic panel models were subsequently used to quantify the importance of financial inclusion and institutional quality. The study employed traditional financial inclusion indicators to construct an index via principal component analysis (PCA). Moreover, the GMM dynamic panel model was employed to evaluate the statistical data. The study found that financial inclusion and institutional quality are positively correlated with economic growth.

Focusing on the Asia-Pacific area, Van et al. (2022) examined the asymmetric effects of institutional quality on financial inclusion. The cited authors sampled 19 countries with data spanning 2004 to 2020 to estimate the financial inclusion index. The rule of law, regulatory quality, government effectiveness, business sophistication, and investment freedom were used as proxies for institutional quality. The panel smooth transition regression technique was employed to ensure that the asymmetric impacts on financial inclusion are substantiated depending on the level of income across the sampled countries. The findings revealed that institutional quality's impact on financial inclusion varies with income level. The findings

further indicate that middle-income countries and other developing countries in the Asia-Pacific region benefit from the positive impact of institutional reform, which ensures future economic growth that is more inclusive.

Nasreen et al. (2023) examined how ICT diffusion and institutional quality affected financial inclusion in 22 Asian economies using data spanning from 2004 to 2020. The study used a composite of six governance indicators to measure institutional quality, while traditional financial inclusion indicators were used to proxy financial inclusion. For empirical analysis, the authors used a panel quantile regression model developed by Powell (Quantile Treat Eff 1(28), 2016). The results underscore ICT's diffusion and institutional quality role in advancing financial inclusion by demonstrating their significant impact on both aggregated and disaggregated metrics of financial inclusion in the Asian region.

To examine the effect of governance on financial stability and financial inclusion, Malik et al. (2022) employed a system GMM estimation technique. The mediating function of financial inclusion in the association between financial stability and governance quality was investigated using Baron and Kenny's approach. The findings indicate that governance quality positively affects financial stability; however, it negatively impacts financial inclusion. The cited authors concluded that financial inclusion acts as a mediator in the relationship between financial stability and governance quality.

As previously mentioned, strong institutions have the potential to significantly increase digital financial inclusion, particularly in EMDEs, and Asia is no different. Overall, empirical literature for the Asian region illustrates that there has been a positive impact on the institutional quality of digital financial inclusion.

3.6.2 Institutional Quality and Digital Financial Inclusion in Southeastern Europe

There is a dearth of research on the effect of institutional quality and digital financial inclusion in the South-Eastern Europe region. This is because, in contrast to traditional finance, digital financial inclusion is a relatively new phenomenon. Analysing its complex relationship with institutional quality is still a work in progress. Moreover, comprehensive research attempts are impeded by the lack of available data. However, only a few studies attempt to demonstrate this relationship.

Indeed, the region of South-Eastern Europe has made great strides toward fostering the growth of the private sector through privatisation, improved economic conditions, and deregulation (Kaditi, 2013). Nonetheless, corruption and limited financial access are still considered to be some of the major investment barriers in the region. Kaditi (2013) investigated whether, and to what degree, strong institutions and regulation levels discourage Foreign Direct Investments (FDI) in four economies in South-East Europe. The researcher employed a dynamic panel analysis and used data spanning 1998 to 2006. The results reveal that foreign capital is strongly impacted by the quality of institutions.

In another study, Corrado (2020) proposed an analytical framework for evaluating households' access to formal credit in European transition economies. The study also took into consideration the perceived quality of institutions in addition to the perceived quality of institutions in addition to the demographic and socioeconomic factors at the individual level. The study aimed to determine whether people's subjective assessment of their own country's political environment and their individual experiences with corruption should be taken into consideration when designing an effective policy intervention to promote financial inclusion. Corrado (2020) constructed a bivariate probit model to account for joint access to credit products that are both short-term and long-term. The findings revealed that enhancing people's access to financial markets throughout the regions in Europe necessitates a range of institutional and local measures that connect financial integrity and financial inclusion policies.

Using fixed effect regression and two-stage least squares (2SLS) regression techniques, Khan et al. (2023) examined the impact of institutional quality on financial system efficiency. A panel dataset covering 108 countries spanning from 1996 to 2020 was used. The findings of the study reveal that every institutional quality component has a positive effect on financial system efficiency.

3.6.3 Institutional Quality and Digital Financial Inclusion in Africa

Chinoda and Kapingura (2024) investigated the impact of institutions and governance on the relationship between digital financial inclusion and economic growth in Sub-Saharan Africa (SSA). The study used a period from 2014 to 2020 and employed the generalised method of moments technique. The four main variables were gross domestic product per capita growth, digital financial inclusion index, governance and institutions. The findings indicate that

institutional quality and governance have a significant positive impact on the relationship between digital financial inclusion and economic growth in SSA.

Doku et al. (2023) examined how the quality of institutions impacts the relationship between digital financial technology and the financial inclusion level in 34 SSA countries using data from 2004 to 2021. Six traditional financial inclusion indicators were gathered to generate a financial inclusion index as well as six variables for institutional quality (corruption control, government effectiveness, political stability, regulatory quality, rule of law, and voice and accountability). For digital finance technology, mobile cellular subscriptions per 100 people, fixed broadband subscriptions per 100 people, internet % of the population, and fixed telephone subscriptions per 100 people were employed. The two-stage system GMM results demonstrate that digital finance technology positively and significantly affects financial inclusion. Moreover, the presence of institutions that are of high quality strengthens the beneficial relationship between digital finance technology and financial inclusion, highlighting the importance of institutional quality in fostering digital finance and promoting financial inclusion.

Markjackson and Timipa (2023) assessed how access to financial services and products in SSA is impacted by institutional quality. The researchers specifically studied the impact of regulatory quality, political stability, and the absence of violence on the penetration of banks in SSA. Panel data was gathered from 12 SSA countries between 2006 and 2021. The findings suggest that in SSA, access to financial products and services is significantly impacted by regulatory quality. Additional findings revealed that in SSA, access to financial products and services is significantly and adversely affected by political stability.

Using autoregressive distributed lag (ARDL) as an estimation technique, Akintunde and Aribatise (2022) investigated the relationship between institutional quality, financial inclusion and the formal economy in Nigeria. The study employed traditional financial inclusion indicators such as the number of commercial bank branches per 100,000 adults and private credit by deposit money banks as a % of GDP. For institutional quality, democratic accountability, corruption control, and law and order were used. The period considered was from 1991 to 2020. The study discovered that the relationship between financial inclusion and institutional quality has a positive and significant impact on Nigeria's informal economy, indicating that poor institutional quality hurts financial inclusion and contributes to the expansion of the informal economy in the country.

In a similar study, empirical evidence from Anthony-Orji et al. (2019) showed that institutional quality has a significant effect on financial inclusion both in the long-run and short-run periods. The study employed the autoregression distributed lag model based on the unrestricted error correlation model (ARDL-UECM) to examine the linkages between institutional quality and financial inclusion in Nigeria. The researchers used quarterly data from 1986 to 2013.

Kwenda and Chinoda (2019) examined the effect of governance and institutional quality on financial inclusion in Africa. The study employed a system GMM estimation technique for panel data from 49 countries from 2004 to 2016. The findings indicate that institutional quality and governance have a positive effect on financial inclusion in the region. The study also established that the size of the banking industry and the lagged value of financial inclusion had a significant positive impact on financial inclusion in African countries.

In another study, Ajide (2017) investigated financial inclusion determinants by focusing on the institutional role. The cited scholar used a panel of 18 countries in SSA covering the period 2004-2010 and applied the system GMM estimation technique. The study used traditional financial inclusion indicators such as ATMs per 100,000 adults, bank branches per 100,000 adults and ATMs per 1,000 km^2. For institutional quality, the six aggregate indicators (Voice and Accountability, Regulatory Quality, Rule of Law, Control of Corruption, Government Effectiveness and Political Stability) were employed. The results indicate that institutions, along with other control variables such as GDP per capita, inflation, bank concentration, and z-score, are important financial inclusion drivers.

Using a sample of 51 African countries, Nkoa and Song (2020) examined the impact of institutional quality on financial inclusion. Traditional financial inclusion indicators such as the number of ATMs per 1000 inhabitants (access dimension), number of active mobile phone accounts per 1000 inhabitants (usage dimension), and number of bank branches per 1000 inhabitants (penetration dimension) were employed as well as six institutional quality variables (voice and accountability, political stability and absence of violence/terrorism, government effectiveness, regulatory quality, rule of law, control of corruption). The study employed a system GMM estimation technique using a period of 14 years (200- 2018). The results reveal that institutional quality increases financial inclusion in Africa.

Contrary to the empirical evidence shared in the above studies, some researchers have found mixed results when assessing institutional quality and financial inclusion. For instance, using

panel data for 17 African countries, Kebede et al. (2021) investigated how the presence of foreign banks affects the various aspects of financial inclusion using data from 2004 to 2018. The study constructed a multidimensional financial inclusion index using a two-stage PCA and further checked for robustness by employing a system GMM. The cited authors demonstrated that the impact of foreign bank presence on financial inclusion is influenced by institutional quality, with its impact changing from detrimental to beneficial as institutional quality rises to a higher degree.

Based on the foregoing, there has been an overall positive impact of institutional quality on financial inclusion in the African region. However, most studies in the existing literature have focused more on traditional financial inclusion as opposed to digital financial inclusion. This is the case, though studies have demonstrated that, in comparison to traditional institutions, digital financial services have been found to deepen financial inclusion, particularly for the underserved population.

3.7 Summary of the Empirical Review Findings

Several studies have been conducted on financial inclusion and institutional quality. However, studies evaluating the effect of institutional quality on digital financial inclusion could not be found. Moreover, EMDEs have not been well covered in the existing literature. Although EMDEs are not as advanced as developed markets, they are in a critical phase of rapid development, where institutional quality is crucial for fostering lucrative outcomes from a rapidly expanding financial sector (Alawi et al., 2022). This gap underscores the need to advance knowledge in this area – hence the current study.

3.8 Methodology: Modelling Institutional Quality and Digital Finance in EMDEs

This section describes the data used and their sources. It also provides an overview of the variables and methods employed for the analyses of the study. This section is divided into four parts: data selection and sources, model specification, measurement of the model, and estimation techniques.

3.8.1 Theoretical Framework and Hypotheses

The analytical methods employed in this study attempt to empirically test the following hypothesis:

H_0: There is no impact of institutional quality on digital financial inclusion in emerging and developing economies.in selected EMDEs.

H_1: There is an impact of institutional quality on digital financial inclusion in emerging and developing economies.in selected EMDEs.

The study starts by using the Principal Component Analysis (PCA) approach to reduce the dimensions of the data. PCA is a statistical technique that reduces the dimensionality of large datasets to their principal components, or key attributes, minimises information loss while also improving interpretability, and eliminates any multicollinearity across variables while preserving all variations that might be present in the data (Chinoda & Kapingura, 2024; Greenacre et al., 2022; Jolliffe & Cadima, 2016).

This study uses the Panel Autoregressive Distributed Lag Method as the primary technique since it estimates the effect of institutional quality on digital financial inclusion in emerging and developing economies. Additionally, the study employs the panel autoregressive distributed lag (ARDL) bounds test model to identify the long-run relationships and short-run dynamics to investigate the effect of institutional quality on digital financial inclusion in EMDEs.

3.8.2 Data Selection and Sources

This study is quantitative and based on secondary sources. The period stems from 2013 to 2021 due to the data availability of the selected variables in 25 EMDEs. Moreover, the starting year for this research is 2013 as some EMDEs chosen for this study did not have available data before 2013. Table 3.1 highlights the selected regions.

Table 3. 1: Sample Description

Region	No. of Countries in the Region
Central Africa	2
Southern Africa	6
West Africa	10
Oceania	3
West Asia	1
South Asia	2
South-Eastern Europe	1
Total number of countries included in the sample	**25**

Source: Compiled by author

The following data sources were used: The Financial Access Survey of the IMF (FAS-IMF), the Worldwide Governance Indicators (WGI) and the World Development Indicators (WDI). The data spans from 2013 to 2021. Given that the available data for the selected countries is from 2013 to 2021 (that is, 8 years), this presented a problem of having fewer observations and degrees of freedom. To overcome this problem, we opted to transform the existing annual data (data from 2013 to 2021) to quarterly data using *Eviews13* to increase the number of observations by using high-frequency data.

The FAS is a supply-side dataset on access to and use of financial products and services that was introduced in 2009 to help policymakers evaluate and monitor financial inclusion and compare progress to peers. The WGI develops composite indicators representing six key governance dimensions: Rule of Law, Government Effectiveness, Voice and Accountability, Control of Corruption, Regulatory Quality, Political Stability and Absence of Violence/Terrorism. The six key dimensions are derived from more than 30 sources of data that present expert evaluation conducted globally as well as views of numerous survey participants. The WDI represents the World Bank's main collection of development indicators, collated from various reputable and reliable international sources. It offers the most recent and reliable global data.

3.9 Data Selection, Description, and Measurement of Variables

Data selection was based on the various dimensions and indicators that the study used.

3.9.1 Dependent variable: Digital Financial Inclusion

The following dimensions and indicators were used to measure digital financial inclusion.

a) *Access (Penetration of Basic Financial Services)*

Mobile money agent outlets active (per 100,000 adults) and mobile money agent outlets active (per 1,000 km^2) serve as indicators of the access dimension as part of the geographic or demographic penetration (Banna, 2020). These indicators are important and necessary for the internet, mobile money, and mobile banking to be used as new avenues for accessing financial services. Moreover, in several markets, the availability of mobile money agents in remote areas has significantly increased access to financial services (Khera et al., 2021). Data for these indicators were sourced from the FAS-IMF.

b) *Usage*

For the usage dimension, the number of active mobile money accounts (per 1,000 adults), number of mobile and internet banking transactions (during the reference year) per 1,000 adults, and value of mobile and internet banking transactions (during the reference year) (% of GDP) serve as indicators (Banik & Roy, 2023; Banna, 2020). Data for these indicators were sourced from the FAS-IMF.

3.9.2 Main Explanatory Variable: Institutional Quality

Institutional quality is the main explanatory variable in our study. Understanding institutions clarifies why some countries are wealthy while others are not, as well as why some have a political system that enhances while others do not (Grief, 2006). Since institutions are multifaceted, defining institutional quality is challenging (Vasilyeva et al., 2018). Policymakers and academics debate the idea of governance frequently; however, currently, there is no consensus on how to define governance or institutional quality. A vast range of definitions has been provided by different scholars and organisations. For instance, Kaufmann et al. (2011) define governance as the traditions and institutions that govern how authority is exercised in a country. Olander (2019) defines governance as following an impartial standard.

More than 200 countries and territories are covered by the Worldwide Governance Indicators (WGI) project, which provides both aggregate and individual governance indicators

encompassing six governance dimensions since 1996. These dimensions are: Control of Corruption, Government Effectiveness, Political Stability and Absence of Violence/Terrorism, Regulatory Quality, Rule of Law, and Voice and Accountability. dimensions are commonly regarded as the most reliable and accurate measures of institutional quality (Rodríguez-Pose & Di Cataldo, 2015). Kaufmann et al. (2011) divide the six dimensions into three pairs and define them accordingly.

The first pair of indicators assesses the procedure used to select, monitor, and replace governments.

Voice and accountability – capture perceptions of the degree to which people in a country can select their government, freedom of association, freedom of expression, and free media.

Political stability and absence of violence/terrorism – captures perceptions about the possibility that violent or unconstitutional methods, such as terrorism and politically motivated violence, will be used to topple or destabilise the government.

The second pair of indicators evaluate the government's ability to effectively develop and execute sound policies.

Government effectiveness – captures perceptions about the quality of public services, civil service and its level of independence from political pressures, policy formulation and execution, and the credibility of the commitment of the government to these policies.

Regulatory quality – captures perceptions of the ability of the government to develop and execute sound policies and regulations that allow and promote development in the private sector.

The last pair of indicators was designed to assess the extent to which a country's citizens feel obligated by the legal system that is embodied in its institutions.

Rule of law – captures perceptions of the degree to which agents trust and follow social norms, particularly those regarding the quality of the police, courts, contract enforcement, property rights, and the probability of crime and violence.

Control of corruption – captures perceptions of the degree to which public authority is used for private benefit, including both small- and large-scale corruption, as well as the state capture by elites and private interests.

Doku et al. (2023) established that the positive relationship between financial inclusion and digital finance technology is strengthened when high-quality institutions are present, highlighting the role that high-quality institutions play in promoting both financial inclusion and digital finance. Therefore, in this study, it was expected that digital financial inclusion would be affected positively by institutional quality. A solid institutional quality fosters a favourable environment for digital financial inclusion. For instance, strong institutions can stimulate participation in the financial sector by fostering trust and confidence in the sector.

3.9.3 Control Variables

In line with Evans (2015), Kouladoum et al. (2022), and Nsiah et al. (2021), this study further employed the following control variables: Inflation (INF), Broad money to GDP (BM), Education (EDU), GNI per capita (constant 2015 US$), Domestic credit to private sector by banks (% of GDP), Population growth (annual %) (PG), Trade (% of GDP), and General government final consumption expenditure (% of GDP) (GOVEXP). These control variables were obtained from the WDI.

a) *Inflation*

Inflation is the gradual overall increase in the price level of goods and services that reduces purchasing power within an economy (Lim & Sek, 2015). It is used as a measurement of how much the price of a set of products and services has increased over a specific period, typically a year (IMF, 2023). The consumer price index (CPI) calculates the percentage change in the cost of a basket of goods and services that households consume. The CPI is the most widely used measure of inflation. Sha'ban et al.'s (2020) findings support the use of inflation as one of the variables that determines financial inclusion. A strong digital financial landscape can support the emergence of cutting-edge financial products, thus promoting savings and ultimately reducing inflation pressures. Saraswati et al. (2020) established that for countries with high financial inclusion levels, productivity shock reduces output and volatility of inflation. Inflation can affect digital financial inclusion either negatively or positively. For instance, the value of money is greatly diminished by high inflation, which makes it difficult

for low-income households to save and have financial stability. This may ultimately deter them from adopting and using digital financial services and products. On the other hand, for countries with low inflation, it is easier for low-income households to save and have financial stability since the monetary value remains stable. This, in turn, motivates households to make use of digital financial services and products.

b) *Broad money to GDP (BM) (Money Supply)*

Broad money to GDP reflects the amount of money supply concerning the economy itself. Broad money includes demand deposits, other liquid assets, foreign currency deposits, and cash. Evans and Alenoghena (2017) established that broad money to GDP has a positive and significant impact on financial inclusion in Africa. The authors further found that developing internet connectivity is crucial for increasing financial inclusion. Greater access to digital financial services through increased money supply can potentially uplift underserved households and businesses in EMDEs. Therefore, we expect a positive relationship between digital financial inclusion and broad money to GDP.

c) *Education*

The gross enrolment ratio in primary education is used as a measure to determine the proportion of children in primary school as a proportion of the corresponding age group (World Bank, 2022). Financial education aims to facilitate access to formal financial services and products, thus reducing financial exclusion (Grohmann & Menkhoff, 2021). Through education, individuals are equipped with the necessary skills to comprehend, adopt and use digital financial services diligently, thus leading to an increase in digital financial inclusion. Therefore, an increase was expected in the level of education, leading to a positive increase in digital financial inclusion.

d) *GNI per capita (constant 2015 US$)*

Gross National Income (GNI) per capita is calculated by dividing the gross national income of a country by its mid-year population. Using fixed effects estimates, Tsouli (2022) found that financial inclusion is positively impacted by GNI per capita. Indeed, countries that exhibit higher GNI per capita have high levels of internet penetration and ownership of mobile phones.

This makes it easier to access digital financial services available online. Therefore, a positive relationship between GNI per capita and digital financial inclusion was expected.

e) *Domestic Credit to the Private Sector by Banks (% of GDP)*

Credit provided to the private sector refers to financial products offered by the depository corporations to the private sector; these financial products include purchases of nonequity securities, loans, trade credits, and other accounts receivable (World Development Indicators, 2022). In their global assessment of financial inclusion, Demirgüc-Kunt and Klapper (2013) found a positive relationship between credit provided to the private sector and financial development. Digital financial services usually have lower costs relative to tools offered by traditional banks. This can make credit more accessible and affordable, especially to underserved individuals. A positive relationship was expected between domestic credit to the private sector by banks (% of GDP) and digital financial inclusion.

f) *Population growth (annual %) (PG)*

Population growth is a measure reflecting population density or abundance trends, and it indicates whether density and abundance are growing, declining, or stable, as well as the rate at which they change (Sibly & Hone, 2002). According to a 2022 report from the United Nations, the global population has more than tripled since the mid-twentieth century. Moreover, the report states that in November 2022, the world's human population amounted to 8 billion and is expected to increase to 9.7 billion by 2050. Population growth has been used in various studies including Neaime and Gaysset (2018) and Kim et al. (2018). With access to digital financial services, households can enhance their standard of living and make better decisions about family planning and their living circumstances. Khera et al. (2021) established that in countries where the population is already accustomed to using traditional financial services, digital financial services are filling the void created by the limited supply of traditional financial services. Therefore, a positive relationship was expected for this variable.

g) *Trade (% of GDP)*

Trade openness refers to the outcomes of a process intended to lower international trade barriers between countries (Mulungula & Nimubona, 2022). Hajilee and Niroomand (2019) argue that the more developed a country's financial market inclusion is, the greater its financial market

development and, ultimately, trade openness. Countries with higher trade openness tend to outperform those with lower openness in terms of economic growth as they can benefit from the transfer of technology from well-developed countries (Keho, 2017).

h) *General Government Final Consumption Expenditure (% of GDP) (GOVEXP)*

General government final consumption expenditure (% of GDP) encompasses current expenditures for all governments for buying goods and services. Government expenditures have a crucial role in promoting economic growth and the well-being of its citizens (Simatupang, 2020). Government expenditure is typically split into current expenditure and capital expenditure. Current expenditure pertains to the everyday operating expenses of the government. These costs include wages, salaries, supplies, etc. On the other hand, capital expenditure is defined as spending on assets that are typically long-term and encompass things like infrastructure (for instance, schools, roads, and bridges), machinery, and other expenditures that promote a country's economic growth and development (Akanbi, 2019; Poku et al., 2022). Empirical evidence from Poku et al. (2022) suggests that there is a positive relationship between government expenditure and economic growth in the short run. Government initiatives that promote financial education and access to digital financial services and products have the potential to effectively drive and increase digital financial inclusion, therefore leading to increased economic growth. A positive outcome was expected for this variable.

Table 3. 2: Summary of the Independent Variables' Prior Expectational Indications

Variable	Description	Expectation Indication	Data Source
IQ	Institutional Quality	Positive (+)	WGI
INF	Inflation	Positive (+) / Negative (-)	WDI
BM	Broad money to GDP	Positive (+)	WDI
EDU	Education	Positive (+)	WDI
GNI	GNI per capita (constant 2015 US$)	Positive (+)	WDI
DCPS	Domestic credit to private sector by banks (% of GDP)	Positive (+)	WDI
PG	Population growth (annual %)	Positive (+)	WDI
TO	Trade Openness (% of GDP)	Positive (+)	WDI
GOVEXP	General government final consumption expenditure (% of GDP)	Positive (+)	WDI

Source: Author's expectations

3.9.4 Data Transformation

Given the relatively short time span of the available annual data (2013–2021), which limited the number of observations and degrees of freedom, the annual data were converted to quarterly frequency using EViews 13. This transformation was necessary to enhance the robustness of the panel ARDL estimation by increasing the N×T dimensions, thereby improving the power of cointegration tests and the reliability of short- and long-run parameter estimates.

To ensure the temporal disaggregation preserved the underlying economic relationships and avoided introducing spurious high-frequency variation, the Denton method (Denton, 1971) was employed. This method is widely recommended by international statistical agencies such as the IMF and Eurostat for converting low-frequency data to higher frequencies when no related high-frequency indicator series are available (IMF, 2017).

The Denton method minimizes the sum of squared differences in the period-to-period changes of the interpolated series, subject to the constraint that the quarterly values sum to the observed annual totals. This approach ensures that the quarterly series maintains a smooth progression consistent with the annual benchmarks, thereby minimizing spurious volatility and preserving the long-run properties of the data.

Justification for Using the Denton Method:

- The method is particularly suitable when no correlated high-frequency indicators are available for all variables across all countries, a common limitation in cross-country panels of EMDEs.
- It avoids the over-reliance on potentially weak or mis-specified related indicators, which can introduce bias in models such as the Chow–Lin method (Chow & Lin, 1971).
- The Denton method is robust and has been extensively applied in official statistics and macroeconomic modelling where temporal consistency with annual benchmarks is critical (Bloem et al., 2001; IMF, 2017).

All variables were disaggregated using this procedure in EViews 13, with the annual totals enforced as binding constraints. The resulting quarterly series were then used in the panel ARDL estimations.

3.9.5 Panel Unit Root Tests

This study examined the stationarity of the data using the most recent and efficient panel unit roots methodologies before starting the estimation process. In probability theory and statistics, time series models can provide challenges when concluding unit roots (Hashemizadeh et al., 2023). On the other hand, the foundation of a panel unit root test is the presumption that cross-sectional units are independent in the first generation and dependent in the second generation. This study employed the LLC (Levin, Lin & Chu, 2002) and IPS (Im, Pesaran & Shin, 2003) tests.

3.9.6 Principal Component Analysis

Using the approach of Camara and Tuesta (2014), the present study employed a two-stage Principal Component Analysis (PCA) to construct a new digital financial inclusion index. Constructing a financial inclusion index for EMDEs allows for the assessment of these countries' progress over time. This offers the possibility of comparing financial inclusion levels across countries. The PCA technique minimises information loss while reducing the number of variables reflecting the same concept (Datta & Singh, 2019).

The PCA technique can decrease data sets to smaller dimensions while retaining as much of the original data as possible. Additionally, PCA scientifically calculates the weights for each dimension instead of manually assigning them and it also eliminates the correlated variables that don't contribute to any decision-making. Moreover, using a two-stage PCA reduces the likelihood of the PCA being skewed towards the weight of the indicators for a given dimension. The PCA method is demonstrated below:

a) *The First Stage of PCA: Estimate the Dimensions (Access and Usage)*

This study used indicators for access and usage dimensions in line with Khera et al. (2021). Essentially, the two endogenous variables Y^a and Y^u are unobserved for each index and must be estimated using their corresponding parameters (τ and δ), in the equation that follows:

$$DFI_i = w_1 Y_i^a + w_2 Y_i^u + e_i \quad (1)$$

where DFI is the digital financial inclusion index of country i

e_i is the variation due of error

$w_1, w_2,$ represent the weights of each dimension; and

Y_i^a, Y_i^u represent dimensions for access and usage. These dimensions are further computed as:

Y_i^a =τ1 Mobile Money Agent Per 100000 Adults + τ2 Mobile Money Agent Per 1000km^2 + e_i (2)

Y_i^u =δ1 Active Mobile Money + δ2No Of Internet Banking Transactions + δ3 Value Of Internet Banking Transactions + e_i (3)

Significant differences exist between country-specific values of the various financial inclusion indicators. Therefore, the Min-Max approach is used to normalise the dataset to improve data comparability. By subtracting the minimum value and dividing it by the range of the indicators' values, this procedure puts all the distinct indicators within an equal range between 0 and 1(Le, Chuc & Taghizadeh-Hesary, 2019). The normalisation formula is presented in equation (5) below:

$$X_{i,d} = \frac{(x_i - m_i)}{(M_i - m_i)} \quad (4)$$

Where x_i indicates the value of indicator *i,* m_i is the minimum value of indicator *i* and M_i is the maximum value of dimension *i*. $X_{i,d}$ represents the standardised value of indicator *i* of dimension *d.*

The estimator of each dimension is represented by the following weighted averages.

$$Y_i^a = \frac{\sum_{j,k=1}^{p} \lambda_j^a PC_{ki}^a}{\sum_{j=1}^{p} \lambda_j^a} \quad (5)$$

$$Y_i^u = \frac{\sum_{j,k=1}^{p} \lambda_j^u PC_{ki}^u}{\sum_{j=1}^{p} \lambda_j^u} \quad (6)$$

The correlation matrix is defined as Rp (pxp) of the *p* standardise indicators for each dimension. λ_j (j =1,…,p) is described as the jth eigenvalue of each of the dimensions. *j* represents the number of principal components (PC). The first PC accounts for the greatest degree of variation in the explanatory variables. γj(px1) is the eigenvector of the correlation matrix. The assumption made is that λ1 >λ2 >⋯>λp and represents where P_k (k=1,…,p) as the *k-th PC* (weights)

b) *The Second Stage of PCA*

After getting the dimension indices, another PCA is conducted to determine the weights for financial inclusion. The overall financial inclusion index is computed by combining all the separate indices into equation (1) to estimate the parameter (λ), that is:

$$TFI_i = \frac{\sum_{j,k=1}^{p} \lambda_j PC_{ki}}{\sum_{j=1}^{p} \lambda_j} \quad (7)$$

PC_{ki} (which represents each component) is expressed as a linear combination of the three dimensions and their respective eigenvectors of the correlation matrices as follows:

$$PC_{1i} = \pi_{11} Y_i^a + \pi_{12} Y_i^u \quad (8)$$

$$PC_{2i} = \pi_{21} Y_i^a + \pi_{22} Y_i^u \quad (9)$$

By replacing the PC_{ki} as written in equations (8) and (9), the financial inclusion index can therefore be expressed as

$$TFI_i = \frac{\sum_{j=1}^{3} \lambda_j (\pi_{j1} Y_i^a + \pi_{j2} Y_i^u)}{\sum_{j=1}^{3} \lambda_j} \quad (10)$$

Equation (10) can thus be written as a linear equation for the weighted average of the financial inclusion index:

$$DFI_i = w_1 Y_i^a + w_2 Y_i^u + e_i \quad (11)$$

The digital financial inclusion index is then used to classify the various countries into three groups.

As per Sarma (2008), the financial inclusion index is then used to classify the various countries into three groups.

$0.5 < DFI \leq 1$ illustrates high digital financial inclusion.

$0.3 \leq DFI < 0.5$ demonstrates medium digital financial inclusion.

$0 \leq DFI < 0.3$ shows low digital financial inclusion.

c) *Indexing Institutional Quality*

$$IQ_i = W_1 CC_i + W_2 GE_i + W_3 PS_i + W_4 RQ_i + W_5 VA_i + W_6 RL_i$$

Where; IQ_i is the index for the i^{th} year and W_1, W_2,…,W_6 are the respective weights of different factors. CC, GE, PS, RQ, VA and RL denote the control of corruption, Government effectiveness, Political stability and absence of violence/terrorism, Regulatory quality, Rule of law, and Voice and accountability, respectively.

3.9.7 Using Panel Autoregressive Distributed Lag Method

This study employs the panel autoregressive distributed lag (ARDL) bounds test model to identify the long-run relationships and short-run dynamics to investigate the effect of institutional quality on digital financial inclusion in EMDEs. The ARDL was developed by Pesaran and Shin (1995), Pesaran (1997), and Pesaran et al. (2001).

Relative to other more established and traditional co-integration techniques, this estimating method has a few advantages. First, the panel ARDL can be applied whether the underlying variables are integrated of order one, order zero, or fractionally integrated, and all the variables under consideration don't need to be integrated in the same order. Second, this technique is comparatively more effective when there are finite and small sizes (Raji, 2021) relative to other cointegration techniques such as the Johansen Test. Third, the traditional cointegration approaches estimate long-run relationships within the context of system equations, and the ARDL procedure uses a single reduced-form equation (Ozturk & Acaravci, 2010). Lastly, in contrast to traditional cointegration techniques, the ARDL estimation technique permits the variables to have distinct optimal lags (Ozturk & Acaravci, 2010).

The ARDL technique can also handle endogeneity and serial correlation problems amongst variables. Therefore, the ARDL technique was suitable for this study as it sought to find short and long-run cointegration between institutional quality and digital financial inclusion in EMDEs.

Following Pham and Doan (2020), the model is estimated as follows:

$$DFI_{it} = f(IQI_{it}, X_{it}) \quad (12)$$

Where; DFI_{it}, IQI_{it}, and X_{it} represent digital financial inclusion variables at time *t* for country *i,* institutional quality variables at time *t* for country *i,* and any other control variables that contribute to digital financial inclusion apart from institutional quality at time *t* for country *i,* respectively.

Due to the above, inflation (INF), broad money to GDP (BM), education (EDU), GNI per capita (GNI), domestic credit provided by the private sector (DCPS), population growth (PG), trade openness (TO), and government expenditure (GXP), are thus included in equation (23) as control variables.

$DFI_{it} = f(IQ_{it}, INF_{it}, BM_{it}, EDU_{it}, GNI_{it}, DCPS_{it}, PG_{it}, TO_{it}, GOVEXP_{it,})$ (13)

Equation (13) is then transformed and expressed as a stochastic equation in equation (14)

$$DFI_{it} = \beta_0 + \beta_1 IQI_{it} + \beta_2 INF_{it} + \beta_3 lnMB_{it} + \beta_4 lnEDU_{it} + \beta_5 lnGNI_{it} + \beta_6 lnDCPS_{it} + \\ + \beta_7 PG_{it} + \beta_8 lnTO_{it} + \beta_9 lnGOVEXP_{it} + \varepsilon_t \quad (14)$$

Where $\beta_1 \ldots \beta_6$ are coefficients, DFI_{it} denotes digital financial inclusion, IQI_{it} is the institutional quality, INF_{it} is inflation, BM_{it} is broad money to GDP, EDU_{it} *is* education, GNI_{it} is GNI per capita, $DCPS_{it}$ *is the* domestic credit provided by the private sector, PG_{it} is the population growth, $GOVEXP_{it}$ is the government expenditure, respectively.

The panel ARDL model is defined by incorporating lags of the dependent and independent variables for both the short-run and long-run co-integration between DFI and IQI, albeit with additional control variables.

From equation (14):

$$DFI_t = \beta_0 + \sum_{i=1}^{\rho} \beta_1 IQ_{t-1} + \sum_{i=0}^{k_1} \beta_2 INF_{t-1} + \sum_{i=0}^{k_2} \beta_3 BM_{t-1} + \sum_{i=0}^{k_3} \beta_4 EDU_{t-1} + \\ \sum_{i=0}^{k_4} \beta_5 GNI_{t-1} + \sum_{i=0}^{k_5} \beta_6 DCPS_{t-1} + \sum_{i=0}^{k_6} \beta_7 PG_{t-1} + \sum_{i=0}^{k_7} \beta_8 TO_{t-1} + \\ \sum_{i=0}^{k_8} \beta_9 GOVEEXP_{t-1} + \varepsilon_t \quad (15)$$

Where; ρ represents the lag of the dependent variable, and k_1 $k_1 \ldots k_5$ is the maximum lags for the independent variables (IQ_{it}, INF_{it}, BM_{it}, EDU_{it}, GNI_{it}, $DCPS_{it}$, PG_{it}, TO_{it}, $GOVEXP_{it,}$)

Equation (26) is specified below to test for cointegration through the panel ARDL bound test:

$$\Delta DFI_t = \beta_0 + \sum_{i=1}^{\rho} \beta_1 \Delta IQ_{t-1} + \sum_{i=0}^{k_1} \beta_2 \Delta INF_{t-1} + \sum_{i=0}^{k_2} \beta_3 \Delta BM_{t-1} + \\ \sum_{i=0}^{k_3} \beta_4 \Delta EDU_{t-1} + \sum_{i=0}^{k_4} \beta_5 \Delta GNI_{t-1} + \sum_{i=0}^{k_5} \beta_6 \Delta DCPS_{t-1} + \sum_{i=0}^{k_6} \beta_7 \Delta PG_{t-1} + \\ \sum_{i=0}^{k_7} \beta_8 \Delta TO_{t-1} + \sum_{i=0}^{k_8} \beta_9 \Delta GOVEEXP_{t-1} + \beta_1 IQI_{it} + \beta_2 INF_{it} + \beta_3 lnMB_{it} + \\ \beta_4 lnEDU_{it} + \beta_5 lnGNI_{it} + \beta_6 lnDCPS_{it} + + \beta_7 PG_{it} + \beta_8 lnTO_{it} + \beta_9 lnGOVEXP_{it} + \varepsilon_t \quad (16)$$

Where; β_1,…, β_6 are coefficients of the short-run dynamics and β_7,…, β_{12} are coefficients of the long-run relationship between variables. ln represents the natural log of the variables and Δ represents the difference indicator.

As per Westerlund (2007) and Engle and Granger (1987), an Error Correction Model (ECM) is introduced in equation (27) to test how the study's variables will converge towards equilibrium in the long run.

$$\Delta DFI_t = \beta_0 + \sum_{i=1}^{\rho} \beta_1 \Delta IQ_{t-1} + \sum_{i=0}^{k_1} \beta_2 \Delta INF_{t-1} + \sum_{i=0}^{k_2} \beta_3 \Delta BM_{t-1} + \sum_{i=0}^{k_3} \beta_4 \Delta EDU_{t-1} + \sum_{i=0}^{k_4} \beta_5 \Delta GNI_{t-1} + \sum_{i=0}^{k_5} \beta_6 \Delta DCPS_{t-1} + \sum_{i=0}^{k_6} \beta_7 \Delta PG_{t-1} + \sum_{i=0}^{k_7} \beta_8 \Delta TO_{t-1} + \sum_{i=0}^{k_8} \beta_9 \Delta GOVEEXP_{t-1} + \lambda ECT_{t-1} + \varepsilon_t \quad (17)$$

Here, ECT and λ represent the error correction term of the relationship between the variables and the speed of adjustments of the long-run equilibrium due to any shocks.

3.10 Empirical Results and Discussion

This section presents data analysis for estimated variables, detailing the digital financial inclusion index construction via PCA, descriptive statistics and diagnostic tests, and the impact of institutional quality on digital financial inclusion using panel ARDL.

3.10.1 Descriptive Statistics

Table 3. 3: Summary Statistics for Digital Financial Inclusion Dataset

Variables	Observations	Mean	Standard deviation	Minimum	Maximum
DFII	900	0.1297	0.1044	0.0085	0.4831
IQI	900	0.0356	0.9931	-2.0478	2.6695
INF	900	8.1136	38.0984	-3.2334	557.2018
BM	900	44.4578	27.7582	14.3793	159.9491
EDU	900	101.4167	16.5994	64.7559	139.5660
GNI	900	6328.6900	10331.9600	1133.4550	96000.0000
DCPS	900	28.1523	21.5562	5.2019	104.8486
PG	900	2.1785	1.3046	-0.9269	11.7940
TO	900	68.8587	26.9942	24.7016	146.4021
GOVEXP	900	15.9226	7.1282	5.1161	40.5535

DFII: Digital Financial Inclusion Index; IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); DCPS: Domestic credit to private sector by banks (% of GDP); PG: Population growth (annual %); TO: Trade Openness (% of GDP); GOVEXP: General government final consumption expenditure (% of GDP).

Source. Calculated by the author using Stata 18

Table 3.3 illustrates that digital financial inclusion has a mean value of 0.1297 and a standard deviation of 0.1044. Further, the minimum and maximum values are recorded at 0.0085 and 0.4831, respectively. Although this variable is stable, the low average financial inclusion index illustrates that the digital financial inclusion level is low in the EMDEs selected for this study. This finding is also affirmed by Naumenkova et al. (2019), who noted that there are many people in low or middle-income countries that are not banked.

Institutional quality has a mean value of 0.0356 and a standard deviation of 0.9931. This suggests that the average level of institutional quality is slightly above zero, indicating a generally positive but modest institutional environment across the EMDEs. The standard deviation of 0.9931 signifies a considerable degree of variability in institutional quality among the EMDEs. This variability is further emphasised by the minimum value of -2.0478 and the maximum value of 2.6695.

Inflation exhibits a mean value of 8.1136 with a standard deviation of 38.0984. The minimum and maximum are recorded at -3.2334 and 557.2018, respectively. The higher standard deviation shows that inflation is not stable, and variations exist in this variable. Ha et al. (2019) found that in EMDEs, inflation expectations are less stable than in developed economies. Broad money to GDP generated an average of 44.4578 and a standard deviation of 27.7582, illustrating a stable money supply regime. The minimum and maximum values were recorded as 14.3793 and 159.9491, respectively.

Education has a 101.4167 mean value and a standard deviation of 16.5994, suggesting that most people who are of working age are in EMDE and are educated. International donors increasingly advocate for allocating limited government funds to basic education as it provides higher social returns and benefits the poor (Birdsall,1996). EMDEs have made considerable progress in increasing enrolment rates over the years. For instance, the World Bank reported an enrolment rate of 81% in 2018 (up from 40% in 1970) for least-developed countries. The average GNI per capita is $6328.6900 with a standard deviation of $10,331.9600, with a minimum of 1133.4550 and a maximum of 96,000. The higher standard deviation observed in the GNI per capita reveals that there are deviations in the GNI per capita of the chosen EMDEs.

The domestic credit to the private sector by banks (% of GDP) reported a mean value of 28.1523 and a standard deviation of 21.5562. The mean value of 28.1523 indicates that, on average, the domestic credit provided by banks to the sector represents approximately 28.15% of a country's GDP. This suggests a moderate level of financial intermediation between banks and the sector across the EMDEs. The standard deviation signifies a considerable degree of variability in the level of domestic credit to the private sector.

Population growth has an average of 2.1785 and a standard deviation of 26.9942, with a minimum value of -0.9269 and a maximum of 11.7940. Population growth may have a short-term negative impact on economic growth due to youth reliance; however, it has long-term beneficial effects due to labour force growth and increased aggregate demand (Bloom & Freeman, 1988). Trade (% of GDP) has a mean of 68.8587 and a standard deviation of 26.9942, illustrating a stable variable. Trade (% of GDP) exhibits a minimum value of 24.7016 and a maximum of 146.4021. Government expenditure was found to have an average value of 15.9226 and a standard deviation of 7.1282, with a minimum value of 5.1161 and a maximum value of 40.5535.

3.10.2 Unit Root Test Results

Table 3. 4: Unit Root Test Results for Digital Financial Inclusion Dataset

Variable	Levin-Lin-Chui		Im, Pesaran, and Shin	
	Level		Level	
	Constant	Constant +Trend	Constant	Constant +Trend
DFII	-2.94641**	-5.57254***	2.01744	1.98474**
	(0.0016)	(0.0000)	(0.9782)	(0.0236)
IQI	-3.64309***	-4.85729***	-2.26271**	-5.74668***
	(0.0001)	(0.0000)	(0.0118)	(0.0000)
INF	-5.08320***	-4.71611***	-6.37352***	-6.01433***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
BM	-2.97730**	-4.33402***	-1.33435*	-3.63773***
	(0.0015)	(0.0000)	(0.0910)	(0.0001)
EDU	-5.01628***	-3.12664***	-2.69400**	-3.00759**
	(0.0000)	(0.0009)	(0.0035)	(0.0013)
GNI	-4.91147***	-4.60132***	-2.10161	-2.64043**
	(0.0000)	(0.0000)	(0.0178)	(0.0041)
DCPS	-4.37132***	-4.96239***	-2.27232*	-4.14199***
	(0.0000)	(0.0000)	(0.0115)	(0.0000)
	-5.09134***	-5.20262***	-2.03402**	-1.77402**
PG	(0.0000)	(0.0000)	(0.0210)	(0.0380)
	-4.09073***	-3.51064***	-3.04946**	-2.40246**
TO	(0.0000)	(0.0002)	(0.0011)	(0.0081)
	-3.37645***	-3.28046***	-2.29479*	-2.60715**
GOVEXP	(0.0004)	(0.0005)	(0.0109)	(0.0046)

Note: () denote the p-values
****, **, denote the significance at the 1% and 5% levels respectively*
DFII: Digital Financial Inclusion Index; IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); DCPS: Domestic credit to private sector by banks (% of GDP); PG: Population growth (annual %); TO: Trade Openness (% of GDP); GOVEXP: General government final consumption expenditure (% of GDP).

Source: Calculated by the author in Stata 18

The study employed the Levin-Lin-Chui (LLC) and the Im, Pesaran, and Shin (IPS) unit root tests. Both tests indicate that digital financial inclusion, IQI, INF, BM, EDU, GNI, DCPS, PG and the GOVEXP are all stationary at level [I (0)] and trend, indicating that they are reliable, valid, and appropriate for the study, and thus did not generate spurious results.

3.10.3 Panel Cointegration Test– Westerlund Test

Table 3. 5: Westerlund Test

Westerlund test for cointegration		
	Statistic	p-value
Variance ratio	2.0135	0.022

To test for the presence of a long-run relationship among the variables, the Westerlund (2007) error-correction-based panel cointegration test was applied. This test is particularly robust as it allows for cross-sectional dependence and panel-specific cointegrating vectors. The test results, summarised in Table 3.14, provide strong evidence against the null hypothesis of no cointegration. The variance ratio statistic of 2.0135 is statistically significant at the 5% level (p-value = 0.022). This confirms that the variables share a stable, long-run equilibrium relationship across the panels.

3.10.4 Multicollinearity – Variance Inflation Factor

The VIF was employed to test for multicollinearity. The results show the independent variables' VIFs below are less than 10, indicating no multicollinearity (see Table 3.6).

Table 3. 6: Variance Inflation Factor Test

Variables	**VIF**	**1/VIF**
DCPS	7.01	0.1427
BM	5.21	0.1920
IQI	2.4	0.4171
TO	2.19	0.4574
GOVEXP	1.88	0.5330
GNI	1.86	0.5369
PG	1.23	0.8145
EDU	1.19	0.8437
INF	1.06	0.9432
Mean VIF	**2.67**	

DCPS: Domestic credit to private sector by banks (% of GDP); BM: Broad money to GDP; Institutional Quality Index; TO: Trade Openness (% of GDP; GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); PG: Population growth (annual %); EDU: Education; INF: Inflation.

Source. Calculated by the author using Stata 18

3.10.1 Pairwise Correlation Matrix

This section discusses the correlation that exists between the dependent variable (digital financial inclusion) and each of the explanatory variables. The pairwise correlation matrix is presented in Table 3.7 below.

Table 3. 7: Pairwise Correlation Matrix

	DFII	IQI	INF	MS	EDU	GNI	DCPS	PG	TO	GOVEXP
DFII	1									
IQI	0.0543	1								
INF	0.2927	-0.1384	1							
BM	-0.105	0.589	-0.1304	1						
EDU	0.1722	0.05	0.0044	-0.0958	1					
GNI	-0.0865	0.4811	-0.0557	0.6545	-0.1068	1				
DCPS	-0.0884	0.7307	-0.1353	0.7126	-0.0673	0.6508	1			
PG	-0.0679	-0.2747	-0.0095	-0.3249	-0.1828	-0.2558	-0.3217	1		
TO	-0.1747	0.2967	-0.0372	0.2219	0.2467	0.0874	0.2784	-0.1500	1	
GOVEXP	-0.1427	0.0839	-0.1004	0.0362	0.0493	0.0069	0.0746	-0.0441	0.6470	1

DFII: Digital Financial Inclusion Index; IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); DCPS: Domestic credit to private sector by banks (% of GDP); PG: Population growth (annual %); TO: Trade Openness (% of GDP); GOVEXP: General government final consumption expenditure (% of GDP).

Source. Calculated by the author using Stata 18

Table 3.7 above indicates that there is a positive relationship between digital financial inclusion and the institutional quality index. The 0.05 correlation coefficient shows a weak correlation between digital financial inclusion and the institutional quality index. Inflation correlates positively with digital financial inclusion. Nonetheless, the correlation between these two variables is weak at 0.29. The negative correlation coefficient of -0.1 between broad money to GDP and digital financial inclusion shows that there exists a negative and weak relationship between these two variables. Education is positively correlated to digital financial inclusion. The coefficient of correlation of 0.17 reveals a weak positive correlation between education and digital financial inclusion.

The GNI per capita is negatively correlated to digital financial inclusion. The coefficient of correlation indicates that there is a moderate negative relationship between GNI per capita and digital financial inclusion. Domestic credit to the private sector is negatively correlated with digital financial inclusion. The correlation coefficient of -0.09 between the two variables indicates a weak correlation. Trade Openness (% of GDP) is negatively correlated with digital financial inclusion with a weak correlation coefficient of -0.17. General government final consumption expenditure (% of GDP) is negatively correlated to barriers to digital financial inclusion. The correlation coefficient of -0.14 between these two variables indicates that there exists a weak correlation. Multicollinearity does not exist in the data as none of the variables have a correlation coefficient of more than 0.8.

3.10.2 Residual Cross-Section Dependence Test

Table 3. 8: Residual Cross-Section Dependence Test

Residual Cross-Section Dependence Test			
Test	Statistic	df	Probability
Breusch-Pagan LM	35.5178	300	1
Pesaran CD	0.4632		0.6432

Source. Calculated by the author using Eviews 13

The *p*-values of the Breusch-Pagan LM and Pesaran CD tests are greater than 0.05, indicating that the null hypothesis cannot be rejected. This suggests no evidence of cross-sectional dependence.

3.10.3 Estimated Results for Digital Financial Inclusion Index

Before computing the PCA test, it is required to run the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity. The KMO test is used to evaluate the suitability of the sample size for PCA whilst Bartlett's test of sphericity determines the intercorrelation of the indicators chosen for the study. The PCA test can be performed if KMO>=0.5 and X^2 (that is, Chi-square) in Bartlett's test of sphericity is statistically significant. As indicated in Table 3.8, the KMO test for this study is 0.6731, which indicates that the data used for this study is suitable and appropriate. Bartlett's test of sphericity has an X^2 of 3822.988 and a *p*-value of 0.000, which shows that there is no correlation between the selected indicators of the study.

Table 3. 9: Kaiser–Meyer–Olkin Measure and Bartlett's Test of Sphericity

Test	Measure	Financial Inclusion dataset
Kaiser–Meyer–Olkin		0.6731
Bartlett's test of sphericity	Chi-square	3822.988
	Degrees of freedom	45
	p-value	0.000

Source. Calculated by the author using Stata 18

Using STATA 18, a measuring model for constructing a financial inclusion index was carried out. The access (Y^a) and usage (Y^u) dimensions were used in the measurement model. Prior to PCA, indicators were standardised (0-1) to eliminate scale bias, with 0 representing financial exclusion and 1, digital financial inclusion.

Table 3. 10: Principal Components Estimates for Sub-Indices

Component	Eigenvalue	Difference	Proportion	Cumulative
Access dimension				
Comp1 (Mobile money agent outlets active per 100,000 adults)	2.0742	0.8627	0.4148	0.4148
Comp2 (mobile money agent outlets active (per 1,000 km2)	1.2115	0.2970	0.2423	0.6571
Usage dimension				
Comp1 (number of active mobile money accounts per 1,000 adults)	0.9145	0.3165	0.1829	0.84
Comp2 (number of mobile and internet banking transactions)	0.5980	0.3963	0.1196	0.9597
Comp3 (value of mobile and internet banking transactions)	0.2017		0.0403	1

Source. Calculated by the author using Stata 18

The results of the first-stage PCA are illustrated in Table 3.10 above. The eigenvalues of each sub-index and latent variables, access (Y^a) and usage (Y^u) were determined by using the PCA method. Principal components with eigenvalues greater than one are the only ones considered for the analysis, as the component with the highest eigenvalue retains more standardized variance relative to the rest (Kaiser, 1960; Nguyen, 2020). As per Table 3.8, the eigenvalues of the principal components for the two dimensions are as follows: 2.0742, 1.2115 (access); and 0.9145, 0.5980, 0.2017 (usage).

Table 3. 11: Scoring Coefficients for Orthogonal Varimax Rotation (Weights)

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Unexplained
Access dimension						
Mobile money agent outlets active per 100,000 adults	0.6431	-0.0749	-0.0099	-0.2136	-0.7315	0
Mobile money agent outlets active (per 1,000 km^2)	0.4327	-0.2415	0.5877	0.5997	0.2221	0
Usage dimension						
Number of active mobile money accounts per 1,000 adults)	0.6044	0.106	-0.2381	-0.397	0.6397	0
Number of mobile and internet banking transactions	0.1748	0.7167	-0.3735	0.5571	-0.0773	0
Value of mobile and internet banking transactions	-0.0572	0.6413	0.677	-0.356	-0.0212	0

Source. Calculated by the author using Stata 18

The retrieved weights of each of the five indicators are displayed in Table 3.11 above. Considering this, for the access dimension, the weights assigned for the first component are 0.6431 for *mobile money agent outlet active per 100,000* indicators and 0.4327 for *mobile money agent outlet active per 1,000km^2* indicator.

On the other hand, for the usage dimension, the *number of active mobile money accounts per 1,000 adults)* indicator has a higher weight at 0.6040 relative to the *number of mobile and internet banking transactions* indicator *at 0.1748, and value of mobile and internet banking transaction* at -0.0572. This illustrates that the *number of active mobile money accounts per 1,000 adults* indicator is more vital than other indicators defining the usage dimension.

By allocating the weights retrieved above to equations (2) and (3) in section 3.3.5, equations (20) and (21) for access and usage dimensions are derived, respectively:

Y_i^a =0.6431mobile money agent per 100,000 adults + 0.4327 mobile money agent per 100,000 km^2 + e_i (18)

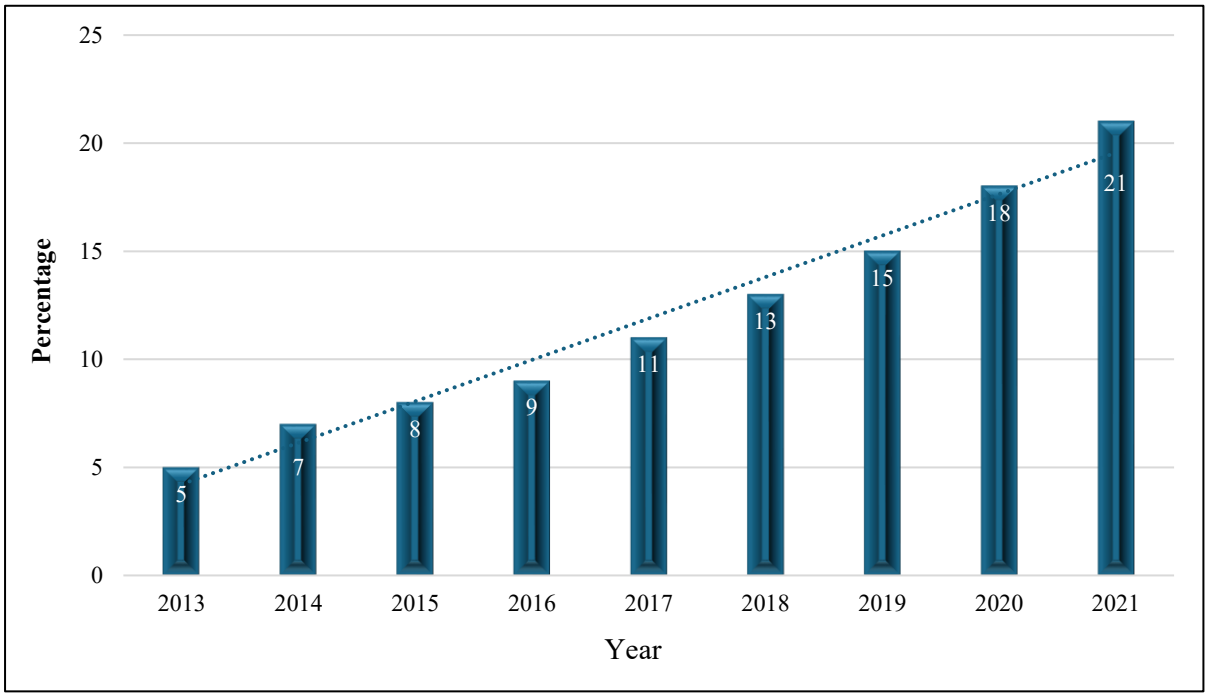
Y_i^u =0.6044active mobile money agent + 0.1748internet banking transactions - 0.0572value of mobile and internet banking transactions + e_i (19)

DFI = [0.6431mobile money agent per 100,000 adults + 0.4327 mobile money agent per 100,000 km^2] + [0.6044active mobile money agent + 0.1748internet banking transactions - 0.0572value of mobile and internet banking transactions] + e_i (20)

Table 3.11 below indicates the digital financial inclusion values as per equation (20) for 25 EMDEs with data from 2013 to 2021. Using the rating scales from Camara and Tuesta (2014), we observe that none of the selected countries in our study exhibited a high degree of digital financial inclusion during the period under review. Zimbabwe and Rwanda demonstrated medium digital financial inclusion levels between 2018 and 2021. Ghana also showed a medium digital financial inclusion level, but only in 2020 and 2021. Furthermore, it is observed that Ghana had the highest digital financial inclusion at 37.9059 in 2021. Jordan demonstrated the lowest digital financial inclusion level from 2013 to 2021. This country's average financial inclusion level was at 4.2708, based on our data. Nonetheless, in terms of the average digital financial inclusion level from 2013 to 2021, all the selected EMDEs fall in the low-level category as their digital financial level is below 30%.

Although the mean values of the selected EMDEs indicate that they fall in the 'low-level' category because their respective means are between 0% and 30%, we observe that the level of digital financial inclusion has been increasing from 2013 to 2021. Khera et al. (2021) and Sahay et al. (2020) established that between 2014 and 2017, digital financial inclusion increased in most of the EMDEs, even in cases where traditional financial inclusion had decreased.

Figure 3. 1: Average Digital Financial Inclusion Levels in EMDEs



Source. Calculated by the author

As shown by Figure 3.1 above, there has been an upward trend in the digital financial inclusion index for EMDEs from 2013 to 2021 due to the increasing significance of institutional quality and digital financial inclusion in EMDEs during the period under review.

As depicted in Table 3.12 and Figure 3.1, the DFII for the selected EMDEs demonstrates a clear upward trajectory from 2013 to 2021. To provide concrete examples, consider the cases of Rwanda, Ghana, and Zimbabwe, countries that transitioned to 'medium' levels of digital financial inclusion during the latter part of the study period. Rwanda's DFII, for instance, rose markedly from 8.82 in 2013 to 37.67 in 2021, a period coinciding with the country's well-documented institutional reforms aimed at improving governance, combating corruption, and fostering a conducive environment for digital innovation. Similarly, Ghana's acceleration in digital finance adoption, evident in its index jump from 20.01 in 2017 to 37.91 in 2021, aligns with significant policy efforts to enhance regulatory quality and promote financial technology.

Table 3. 12: Digital Financial Inclusion Values from 2013 – 2021

Country	Year									Mean	Average Digital Financial Inclusion Level
	2013	2014	2015	2016	2017	2018	2019	2020	2021		
Albania	3.2060	3.7673	4.3303	4.8529	4.8245	4.9286	5.1125	5.3358	5.9467	4.7005	Low
Bangladesh	9.9707	15.0300	15.3785	19.8796	24.7223	24.8288	23.5607	22.6790	27.0455	20.3439	Low
Benin	0.8494	2.9981	5.1419	7.2805	11.4782	15.6542	22.5390	32.7740	35.4537	14.9077	Low
Botswana	6.2219	8.0719	8.4420	9.6677	10.6670	11.5701	16.8367	20.0612	27.2104	13.1943	Low
Burkina Faso	3.8692	4.5883	5.3038	6.0159	8.5670	13.8312	16.6375	18.4882	24.1452	11.2718	Low
Cameroon	4.4849	4.9001	5.8310	5.1802	8.4463	10.3157	13.3597	16.4472	19.5014	9.8296	Low
Côte d'Ivoire	5.5998	6.4342	7.2682	8.1018	13.3050	17.2933	22.3377	26.7631	33.8144	15.6575	Low
Fiji	3.3078	4.0934	4.8786	4.5976	4.7950	4.7482	6.7179	6.8934	7.1851	5.2463	Low
Ghana	4.8008	6.3855	10.2873	15.7032	20.0115	22.6481	25.9437	32.8342	37.9060	19.6134	Low
Guinea	1.0678	2.4680	4.0160	5.9474	7.6022	9.8666	12.5634	15.3101	18.0593	8.5445	Low
Guinea-Bissau	3.8080	3.7914	3.7748	3.7579	4.6934	5.8833	10.8426	19.4031	21.8510	8.6451	Low
Lesotho	4.5769	5.9448	7.6839	8.8344	11.5817	12.5667	14.9574	17.4736	23.9607	11.9533	Low
Malawi	5.8891	6.5073	7.1255	7.7437	8.2475	10.1322	12.3163	17.1468	21.7526	10.7623	Low
Mali	5.7388	6.5825	7.4233	8.2610	8.2056	9.2503	10.4132	13.1505	14.4518	9.2752	Low
Mauritius	9.1510	10.6535	12.1267	13.5691	14.9791	15.4519	20.1929	24.4382	29.2697	16.6480	Low

Niger	5.1307	4.9598	4.7886	4.6172	4.5537	4.3490	4.1043	4.0635	4.8191	4.5984	Low
Rwanda	8.8186	16.4191	18.0736	23.0219	26.9647	31.9171	33.4590	36.8927	37.6738	25.9156	Low
Samoa	4.2813	4.4098	6.0485	5.9946	5.9652	5.6759	6.3065	6.1009	4.6202	5.4892	Low
Senegal	7.2637	7.3549	7.4460	7.5370	9.8203	13.2728	18.1538	18.1981	43.3444	14.7101	Low
Solomon Islands	3.7168	4.1616	4.2407	5.1401	4.9815	4.9798	4.5369	4.7433	4.9480	4.6054	Low
Togo	3.2992	4.1134	4.9276	5.7418	8.2559	8.9544	11.4438	14.1905	16.8488	8.6417	Low
Zambia	4.2811	4.4063	4.5442	5.1890	6.2774	10.7281	15.5617	23.8277	26.7142	11.2811	Low
Zimbabwe	12.3864	14.4626	17.3870	17.1016	26.0552	37.0011	39.7925	37.6548	33.3810	26.1358	Low
Jordan	4.2628	4.0475	3.8311	3.6448	3.9593	4.0661	4.2017	5.0714	5.3529	4.2708	Low
Pakistan	5.0915	5.9564	7.2041	7.0747	7.3707	7.1273	7.5609	8.5701	10.0347	7.3323	Low

Source. Calculated by the author

3.10.4 Panel ARDL Results

Long Run

Table 3. 13: Long-Run Effects: Institutions and Digital Financial Inclusion

Variable	Coefficient	Standard Error	t-Statistic
IQI	0.5887***	0.0126	46.8724
INF	-0.0031**	0.0016	-2.0392
lnBM	-0.0395	0.0844	-0.4683
lnEDU	0.2898**	0.1096	2.6445
lnGNI	0.3515***	0.0506	6.9541
lnDCPS	-0.1364**	0.0525	-2.5988
PG	0.5747***	0.0475	12.0988
lnTO	0.006273	0.0592	0.1059
lnGOVEXP	-0.2716***	0.0647	-4.1951
Constant	5.6168***	1.0696	5.2513

Note: Financial inclusion is the dependent variable
The number of observations is 875
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*
IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); DCPS: Domestic credit to private sector by banks (% of GDP); PG: Population growth (annual %); TO: Trade Openness (% of GDP); GOVEXP: General government final consumption expenditure (% of GDP).

Source: Calculated by the author in Eviews13

This study employed logarithmic transformations for the dependent variable (Digital Financial Inclusion Index) and all continuous, strictly positive independent variables (e.g., Broad Money, GNI per capita, Trade Openness) to facilitate an elasticity interpretation of the long-run ARDL coefficients. Variables that could assume zero or negative values, namely the Institutional Quality Index, Inflation, and Population Growth, were retained in levels, resulting in semi-elasticity interpretations for their coefficients.

Table 3.13 illustrates the long-run results of the panel ARDL technique employed by the study. There are nine variables in the final ARDL model – institutional quality, inflation, broad money to GDP, education, gross national income per capita, domestic credit to private sector by banks (% of GDP), population growth, trade (% of GDP) and general government final consumption expenditure (% of GDP). Table 3.12 further shows that of the nine explanatory variables, seven

of these (that is, institutional quality, inflation, education, gross national income per capita, domestic credit to private sector by banks (% of GDP), population growth, and general government final consumption expenditure (% of GDP)) can reliably explain long-run dynamics regarding digital financial inclusion. The explanatory variables vary in the degree of impact as indicated by the coefficient values.

The results were analysed using the PMG/ARDL type, which can assist in tacking the issues related to stability in the analysis. This indicates that no stability test will be required, and that the dependent variable cannot be impacted in any way by a non-linear combination of the independent variables. An in-depth analysis is provided in the subsequent paragraphs.

a) *Institutional Quality: Positive Impact on Digital Inclusion*

The main explanatory variable (institutional quality) has a positive and significant effect on digital financial inclusion in EMDEs at 1%. The sign and magnitude indicate that when institutional quality increases by a percentage point, the digital financial inclusion index will increase by a magnitude of 0.5887 units in the long run. Strong institutions can assist in ensuring the safety and reliability of digital financial services. This is critical for creating confidence with potential consumers, who might be reluctant to adopt and use digital financial services. Our results are congruent with existing literature, both empirical and theoretical. For instance, theoretically, the findings align with the Neo-intuitional theory (North, 1990), which emphasises the importance of regulations and standards in determining institutional quality.

b) *Legal and Governance Frameworks: Driving Digital Inclusion*

Robust legal frameworks, transparent governance, and regulatory frameworks that are efficient foster a stable and reliable environment that is favourable for the growth of digital financial inclusion, especially in EMDEs. Empirically, the findings are aligned with results from Doku et al. (2023), who established that high-quality institutions reinforce the relationship between digital finance and financial inclusion, highlighting the importance of institutional quality in supporting both. In a similar study, Chinoda and Kapingura (2024) established that institutional quality and governance have a significant positive impact on digital financial inclusion. Based on existing literature and this finding, it is evident that stronger institutions have a favourable impact on digital financial inclusion.

c) *Inflation's Negative Impact on Digital Inclusion*

Inflation as a control variable significantly and negatively affects digital financial inclusion in EMDEs. This signifies that there is an inverse relationship between inflation and digital financial inclusion. For a percentage point increase in inflation, digital financial inclusion will decrease by a small magnitude of 0.0031 in the long run. In developing countries, high inflation has a disproportionately detrimental effect on digital financial inclusion due to poor financial infrastructure, amongst other factors. High inflation typically results in decreased purchasing power for individuals and firms, making it harder for them to afford digital financial services. Nonetheless, Ozili (2018) and Shofawati (2019) argue that in the case of monetary and financial systems, digital financial inclusion decreases the circulation of physical cash and contributes to decreasing inflation rates in EMDEs.

Further, Saraswati et al. (2020) note that increasing financial inclusion can lead to lower inflation rates. Our finding is in line with results from Chinoda and Kapingura (2024), who established that high inflation levels hinder the growth potential of digital financial inclusion. According to the current study, high inflation affects digital financial inclusion negatively. Therefore, EMDES must create an environment that stimulates competition amongst providers of digital financial services, which could drive down costs.

d) *Education Drives Digital Financial Inclusion*

Further findings reveal that education significantly and positively affects digital financial inclusion at a 5% significance level. The sign and magnitude show that when the level of education increases by a percentage point, digital financial inclusion will increase by a magnitude of 0.2898 units in the long run. Improved financial inclusion relies on improved financial literacy, which also increases the likelihood of accessing and using the internet and digital financial services and products (Shen et al., 2020). Education equips individuals with the skills to use digital services and improves their understanding of finances.

Moreover, individuals with high levels of education tend to make better financial decisions, which results in more and improved utilisation of financial services (Hussein, 2020). For instance, people acquire skills in investing, saving, and responsible credit, therefore increasing their likelihood of successfully adopting and using digital financial services. Our outcome is consistent with findings from Akinyemi and Mushunje (2020), Bakhshi and Agarwal (2020),

Eka (2023), and Jaya (2019), who confirm that education is a significant factor in digital financial inclusion.

e) *GNI Per Capita: Positive Impact on Digital Inclusion*

The results reveal that, in the long run, gross national income per capita impacts digital financial inclusion positively and significantly at a 1% significance level in the selected EMDEs. The sign and magnitude demonstrate that the level of digital financial inclusion in EMDEs will increase by 0.3515 for every dollar increase in the per capita income. When countries have higher GNI per capita, they typically have financial systems that are efficient and sophisticated. This helps in supporting the adoption, use, and growth of digital financial services.

Moreover, digital financial services could potentially increase their market share in the financial sector as disposable income increases. Higher-income earners are more inclined to utilise digital financial services as they understand and appreciate the benefits, they have such as speed, convenience, affordability, and efficiency amongst others. This finding is consistent with findings from Tsouli (2022) and Schwegler (2021). The finding further suggests that one of the primary causes of the variations observed in the level of digital financial inclusion in the 25 EMDEs selected for this study may be the GNI per capita variable.

f) *Unexpected Result: Private Credit Hinders Digital Financial Inclusion*

Domestic credit to the private sector by banks (% of GDP) was found to be significant at a 5% significance level. The sign and magnitude suggest that a percentage point increase in domestic credit to the private sector by banks as a percentage of GDP will reduce digital financial inclusion by 0.1364 units. The result is surprising as one would expect that banks' increase in domestic credit to the private sector as a percentage of GDP will increase digital financial inclusion. Nonetheless, crowding out effect may result from high levels of domestic credit to the private sector, whereby financial institutions such as traditional banks increase their credit facility exposures to firms that have some form of security or are perceived to have lower risk, than investing in initiatives meant to advance digital financial inclusion to serve households and firms that do not already have access to financial services. Moreover, financial institutions may have limited funds to invest in the infrastructure required for digital financial services, which is crucial for increasing financial services access to underserved households and firms.

This is especially true if a sizeable portion of their capital is loaned out to well-established businesses.

g) *Population Growth Drives Digital Financial Inclusion*

Population growth was found to be significant at a 1% significance level in the long run. The sign and magnitude indicate that a percentage increase in population growth will lead to a 0.5747 increase in demand for financial services and products, thus encouraging financial institutions to broaden their client base and offer new products and services targeted at individuals who are financially excluded. As already established, digital financial services can close the gap that exists between individuals and firms that do not have access to financial services and traditional financial institutions. An increase in population growth has the potential to lead to an increase in the digital financial services user base, thus essentially increasing digital financial inclusion. This finding corroborates Ahmad et al. (2021), Hashemizadeh et al. (2023), and Evans (2018).

h) *Unexpected Result: Government Spending Negatively Impacts Digital Inclusion*

General government final consumption expenditure (% of GDP) was also found to be significant at a 1% significance level in the long run. The sign and magnitude suggest that a percentage increase in government expenditure will lead to a 0.2716 decrease in digital financial inclusion in EMDEs. This outcome is surprising, as one would expect that an increase in government expenditure will lead to an increase in digital financial inclusion. This is informed by the fact that firms and households with limited or lack of access to traditional financial services can receive digital financial services if the government supports and invests in initiatives such as digital and broadband infrastructure, mobile banking services, and digital literacy programmes.

Nonetheless, the negative impact of government expenditure on digital financial inclusion as indicated by our results may suggest that in some cases, government funding might not get distributed efficiently, leading to wasteful expenditure and ultimately impeding the progress already made on digital financial inclusion. Furthermore, corruption is one of the biggest hindrances to progress in developing countries. Empirical evidence indicates that corruption is more prevalent in EMDEs than in advanced economies (Svensson, 2005; Shabbir and Anwar,

2007; Kenny, 2007). The finding aligns with Bakari et al. (2018), who argue that high levels of government expenditure deter financial inclusion.

The rest of the control variables, broad money to GDP and trade (% of GDP) were, however, found to be insignificant in the ARDL long-run model. This indicates that these variables do not affect digital financial inclusion in EMDEs.

Short Run

Table 3. 14: Short-Run Effects: Effects: Institutions and Digital Financial Inclusion

Variable	Coefficient	Standard Error	t-statistic
ΔIQI	0.2005	0.2870	0.6984
ΔINF	-0.0399*	0.0237	-1.6868
ΔlnEDU	-0.0992	4.6404	-0.0213
ΔlnGNI	-1.0968	1.9395	-0.5654
ΔlnDCPS	-0.2451	0.8622	-0.2843
ΔPG	-0.0326	1.7574	-0.0185
ΔlnTO	0.7767*	0.4427	1.7544
ΔlnGOVEXP	-0.2884	1.1213	-0.2572
Cointegration	-0.0409***	0.01073	-3.8092

Note: Financial inclusion is the dependent variable
The number of observations is 875
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*
IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); DCPS: Domestic credit to private sector by banks (% of GDP); PG: Population growth (annual %); TO: Trade Openness (% of GDP); GOVEXP: General government final consumption expenditure (% of GDP).

Source: Calculated by the author in Eviews13

Table 3.14 illustrates the short-run results of the panel ARDL technique employed by the study. The results further show that of the nine explanatory variables employed, two of these (that is, inflation and trade (% of GDP) can reliably explain short-run dynamics regarding digital financial inclusion. The explanatory variables vary in the degree of impact as indicated by the coefficient values. An in-depth analysis is provided in the paragraphs that follow below.

Inflation significantly and negatively affects digital financial inclusion in the short run at a 10% significance level. This signifies that there is an inverse relationship between inflation and

digital financial inclusion in EMDEs. For a percentage point increase in inflation, digital financial inclusion will decrease marginally by 0.0399 in the short run. Households may place a higher priority on urgent requirements than digital financial inclusion investments during high-inflation times as they would not have sufficient money available for essential items. Furthermore, the price of internet connectivity, cell phones, and the equipment required to engage in a digital financial environment could potentially increase due to an increase in inflation. Jukan et al. (2024) found that countries that exhibit high financial inclusion levels are more resistant to inflation.

Trade (% of GDP) was also found to significantly and positively affect digital financial inclusion in the short run at a 10% significance level. Economic growth is frequently correlated with increased trade. This expansion may encourage investments in digital infrastructure, lowering costs and increasing accessibility for users to engage in the digital financial sector. Moreover, trade can generate new employment prospects and business ventures that require digital financial services, thus enhancing digital financial inclusion. Our results are consistent with findings from Qamruzzaman (2023), who confirms that trade openness is vital in advancing financial inclusion. Therefore, trade (% GDP) should persist in the selected EMDEs to increase digital financial inclusion. In a similar study, Kouladoum et al. (2022) established that financial inclusion is positively and statistically significantly impacted by trade, thus suggesting that trade in goods and services enhances financial inclusion.

The rest of the control variables, institutional quality, broad money to GDP, education, gross national income per capita, domestic credit to private sector by banks (% of GDP), population growth, and general government final consumption expenditure (% of GDP) were however found to be insignificant in the ARDL short-run model. Thus, these variables do not affect digital financial inclusion in EMDEs.

3.5. Concluding Remarks

The study sought to examine the effect of institutional quality on digital financial inclusion in EMDEs in both the short and long run. This was done by employing the panel ARDL technique. Through the perspective of the Neo-intuitional theory (North, 1990), which holds that institutional quality enhances how people operate, and that the system generates better economic returns than any of its pieces could, this chapter has explored the theoretical foundations of the effect of institutional quality on digital finance in EMDEs.

The present study illustrates that access to financial products and services is significantly impacted by regulatory quality. Empirical literature shows that strong institutions play a significant role in fostering digital financial inclusion, hence advancing financial stability and economic progress, particularly across countries in EMDEs. For our selected countries (based on data availability), empirical research shows that institutional quality factors such as corruption control, government effectiveness, political stability, regulatory quality, rule of law, and voice and accountability have been adopted by most studies in the existing literature. However, financial inclusion dimensions and indicators employed by existing literature have primarily focused on traditional financial inclusion and not digital financial inclusion, thus leaving considerable unexplored ground for research to be conducted in this space.

This study constructed a new multidimensional digital financial inclusion index for 25 EMDEs using weights derived from the PCA in aggregating indicators for two dimensions, that is, access and usage, following Camara and Tuesta (2014) and Khera et al., (2022). The index is a useful tool for evaluating the degree of digital financial inclusion in various EMDEs and tracking their development over time. Between 2013 and 2021, none of the countries that were included in our study demonstrated a high level of digital financial inclusion. From 2018 to 2021, Zimbabwe and Rwanda showed a medium degree of digital financial inclusion. Ghana only showed a medium digital financial inclusion level in 2020 and 2021. However, using the average level of digital financial inclusion between 2013 and 2021, all the chosen EMDEs are classified as low-level because their digital financial inclusion is less than 30%. Taking this into consideration, governments and policymakers in the selected countries and other EMDEs with low digital financial inclusion levels ought to make sure that there are available programmes and policies in place to take care of the needs of underserved and marginalised populations, such as women and youth.

The primary objective of this research was to use the panel ARDL technique to investigate how institutional quality affects digital financial inclusion in EMDEs. The study investigated the long-run effect of institutional quality on digital financial inclusion in EMDEs. The study found that institutional quality has a positive and significant effect on digital financial inclusion in EMDEs in the long run. Additionally, some control variables also demonstrated their significance in the long run concerning digital financial inclusion. These include inflation, broad money to GDP, education, gross national income per capita, domestic credit to the private

sector by banks (% of GDP), population growth, trade (% of GDP), and general government final consumption expenditure (% of GDP).

By investing in the development of cost-effective and efficient internet connections, governments and policymakers can play a critical role in promoting digital financial inclusion through financial institutions. Moreover, governments and institutions can collaborate to develop an environment that promotes digital financial inclusion. This enables households and businesses to take advantage of the formal financial system and be part of a thriving and inclusive society. Therefore, governments and policymakers must work together to build robust institutions in EMDEs as this will benefit underserved individuals and ultimately increase financial inclusion in the various countries.

The study further investigated the short-run effect of institutional quality on digital financial inclusion in EMDEs. The study established that inflation and trade (% of GDP) can reliably explain short-run dynamics regarding digital financial inclusion. Governments can partner with FinTech companies that provide affordable digital financial services. This can be very pertinent when it comes to cross-border transactions impacted by trade difficulties. Governments and policymakers can achieve substantial progress toward digital financial inclusion in the short and long run by integrating the above-mentioned tactics. To achieve this, collaboration, prioritizing the development of households and businesses to understand and manage the economic conditions, and coming up with innovative ideas in EMDEs will be essential.

CHAPTER 4

THE EFFECT OF DIGITAL FINANCIAL INCLUSION ON INCLUSIVE GROWTH AND POVERTY IN EMERGING AND DEVELOPING ECONOMIES

4.1 Introduction

Poverty continues to be one of the biggest challenges faced by developing countries as most of the people living in these countries do not have access to essential financial services. For the past 20 years, credit unions, savings cooperatives, and microfinance organizations have made significant strides, yet most of the world's impoverished communities still do not have access to formal financial institutions (Xu et al., 2024). Digital financial services can help alleviate poverty levels by providing impoverished populations with access to basic financial services and products. Through the adoption and use of technology, digital financial inclusion has the potential to end the poverty cycle by liberating previously disadvantaged groups and fostering inclusive growth, particularly in EMDEs.

4.2 Digital Finance: Driving Inclusion and Growth

There is currently no consensus on how to define digital finance, however, there is a general agreement that it encompasses all technology and or infrastructure, products, and services that assist businesses and people in accessing credit facilities, payments, and savings through online channels (Ozili, 2018). Digital finance has attracted a lot of interest from scholars and policymakers as a means of alleviating poverty and increasing financial inclusion. All participants involved in the financial sector, including users of financial services, companies that supply digital financial services (such as application programming interfaces, web, machine learning, and mobile devices), regulators, decision-makers, and the economy benefit greatly from digital finance. By using a branchless technology-based banking system, digital finance can lower the cost of service for banks and FinTech suppliers while increasing access to financial services for the underprivileged and poor (Siddik et al., 2020). Additionally, financial intermediaries can assist in enhancing the poor's access to financial services by decreasing transactions, liquidity risk, and information asymmetry.

This focus on improving access is aligned with the recent recognition of inclusive growth, which posits that economic growth must be more favourable to the poor, improve productivity and increase new job opportunities (Sarpong & Nketiah-Amponsah, 2022). Global dialogues emphasize that EMDEs should strive for inclusive growth that goes beyond economic growth (Kouton, 2019) as economic growth alone is not sufficient to achieve equitable growth. Digital financial inclusion can play a crucial role in fostering inclusive growth in EMDEs by providing access to financial services and products to financially excluded individuals and businesses. By empowering underserved populations through technology and innovation, digital finance not only promotes inclusive growth but also helps alleviate poverty.

4.2.1 Digital Inclusion, Growth, and Poverty: A Research Gap

Most prior research has focused on either the impact of digital financial inclusion on inclusive growth (Khera et al., 2021; Ozturk & Ullah, 2022; Thaddeus et al., 2020; Xun et al., 2020) or the impact of financial inclusion on poverty (Lyons et al., 2020; Koomson et al., 2020; Peng & Mao, 2022; Polloni-Silva et al., 2021). These studies have demonstrated that digital finance does reduce poverty and is closely related to the advancement and expansion of inclusive economic growth. Furthermore, research has revealed that a potent instrument for combating poverty is financial inclusion. However, the existing literature lacks explicit studies examining the effect of digital financial inclusion on both inclusive growth and poverty simultaneously. Put differently, the effect of digital financial inclusion on poverty through the intervention of inclusive growth is not available in the existing literature. Therefore, it is essential to examine how digital financial inclusion impacts poverty through inclusive growth, as these two topics are closely interconnected and important for achieving equitable growth.

Moreover, there is insufficient research on the effect of digital financial inclusion on inclusive growth and poverty from EMDEs' perspective, as most studies have focused on specific countries as opposed to a cross-section with several countries. As a result, there has not been much attention on simultaneously investigating the effect of digital financial inclusion on inclusive growth and poverty in various EMDEs. Due to the higher prevalence of financial exclusion in EMDEs, they require a more thorough investigation as they have not been sufficiently covered in existing literature, thus providing a gap to explore. In the African region, most of the studies found that an increase in digital financial inclusion leads to a decrease in poverty (Kelikume, 2021; Koomson et al., 2020; Lyons et al., 2020; Wale-Awe & Evans, 2023). Similarly, in the Asian region, results from most studies suggest that digital

financial inclusion can significantly lower poverty levels (Peng & Mao, 2022; Tay et al., 2022; Wang & He, 2020; Xie, 2023). Additionally, studies in the African and Asian regions also found that digital financial inclusion significantly and positively affects inclusive growth (Afolabi, 2020; Iddrisu et al., 2023; Sarpong & Nketiah-Amponsah; 2022; Wang & Yu, 2024; Xun et al., 2020; Yang et al., 2024;), which ultimately leads to poverty reduction. Other regions of interest in the current study, such as Oceania and South-Eastern Europe, have received limited to no scholarly attention from existing literature. Therefore, this research will contribute to the scarce literature in these regions. Examining several countries simultaneously can assist us in identifying trends that might not be apparent or too obvious in a single country. This may enable more broadly applicable conclusions regarding our specific topic for this chapter.

4.2.2 Study Contributions: Digital Inclusion, Growth, and Poverty Analysis

The analytical techniques employed in this chapter seek to empirically establish the effect of digital financial inclusion on inclusive growth and poverty in EMDEs. Considering the shortcomings, this study adds to the body of knowledge in four ways.

a) *Methodology Contribution: System-GMM & PCA Index*

First, this study empirically examined the effect of digital financial inclusion on inclusive growth and poverty in EMDEs by employing the System-Generalized Method of Moments (GMM) as the main estimation technique. System GMM offers reliable and effective estimates, solves the endogeneity issue, and better fits panel studies. The study constructs a new digital financial inclusion index by employing the principal component analysis (PCA) approach. The index enables a cross-country comparison of the level of digital financial inclusion and thus provides a consistent method for monitoring progress across various countries.

b) *Contribution: Digital Finance and Poverty Through Inclusive Growth*

Second, the effect of digital financial inclusion on poverty through the intervention of inclusive growth is not available in the existing literature. Therefore, there is a need to examine digital financial inclusion's effect on poverty through the intervention of inclusive growth. Unlike economic growth, inclusive growth ensures that the benefits of the growth of the economy are allocated equitably, thus reducing poverty.

c) *Regional Contribution: Digital Inclusion, Growth, Poverty Analysis*

Thirdly, this study investigates the effect of digital financial inclusion on inclusive growth and poverty in Central Africa, Southern Africa, West Africa, Oceania, West Asia, and South Asia, as there are scarce studies in these regions, and hence they require more consideration.

d) *Methodological Contribution: Justifying Panel Data Use*

Finally, this study employed panel data as it provides more insightful data, improves efficiency, provides more variability, and reduces variable collinearity (Greene, 2005; Gujarati, 2003; Woolridge, 2002). Furthermore, panel data provides a way of managing unobserved countries and or time-specific heterogeneity, which could be correlated with the explanatory variables included in the study (Akbar et al., 2011).

4.2.3 Study Findings: Digital Inclusion, Growth, and Poverty Links

The findings reveal that digital financial inclusion has a positive and significant effect on inclusive growth in EMDEs at a 10% significance level. The sign and magnitude indicate that when digital financial inclusion increases by a percentage point, inclusive growth will increase by 0.7428 units. Digital financial inclusion is crucial to accomplishing inclusive growth as the process and effort of developing a digital society continue to grow (Song et al., 2022).

Moreover, the findings also demonstrate that inclusive growth has a negative and significant effect on poverty in EMDEs at a 5% significance level. The sign and magnitude indicate that when inclusive growth increases by a percentage point, poverty will decrease by a magnitude of 0.0415 units. Concerns over rising inequality despite economic growth have culminated in an increasing awareness of the significance of inclusive growth and development in international development (Kuss et al., 2022).

Investigating the effects of digital financial inclusion on inclusive growth and poverty in EMDEs will enable policymakers and governments to identify relevant paths in which digital financial inclusion fosters inclusive growth and reduces poverty. Additionally, this study can help policymakers and governments to prioritise capital or investments in industries with the greatest prospects of increasing inclusive growth and alleviating poverty.

4.3 Literature Review

This section delves into the foundational concepts and measurements of poverty and inclusive growth. It also explores the theoretical underpinnings of the study, specifically focusing on the Theory of Financial Intermediation, to provide a comprehensive context for the subsequent empirical analysis.

4.3.1 The Concept and Measurement of Poverty

Poverty remains one of the most prevalent and persistent social issues faced by EMDEs (Cobbinah et al., 2013). It is a broadly applied concept in every country in the world, however, there is no consensus on how to define it (Gordon, 2006). Existing literature illustrates that there are numerous types of poverty indicators and definitions available, which can be classified into one of the following three categories:

a) Poverty is not having more than a certain minimum that has been objectively determined,
b) Poverty is not having as much as others in society in relative terms, and
c) Poverty is one feeling that one does not have enough to get by (Panday, 2008; Wijekoon et al., 2021).

The definitions in the first group can be considered absolute poverty, whereas the second group speaks to relative poverty. The third group is a combination of absolute and relative poverty. The United Nations (1995) defines absolute poverty as a state in which there is a severe lack of access to essential human necessities such as clean water, health care, education, food, housing, sanitary facilities, education, and information. Relative poverty is defined by Bellù and Liberati (2005) as one's standard of living relative to other people's income and expenditure allocation.

The concept of poverty in EMDEs is complicated as it involves more than just a lack of economic resources. It is often deliberated at international forums by political leaders and global institutions such as the World Bank, the International Monetary Fund, and the United Nations. Furthermore, the concept of poverty is discussed and evaluated by politicians, scholars, and international institutions to continue to keep the impoverished on the agenda, identify the impoverished to prioritise interventions that aim to alleviate poverty, track and

assess initiatives that focus on the impoverished, and assess the efficacy of institutions whose objective is to help those who live in poverty (Gwariro et al., 2017).

The global poverty statistics are alarming, as approximately 700 million people in 2024 currently live in extreme poverty (World Bank, 2024), meaning their daily income is below $2.15, which the World Bank deems as the extreme poverty line. Combating poverty has been deemed an ethical, political, economic, and social responsibility for humanity owing to its detrimental effects on the well-being of people in general (Ayoo, 2022; World Bank, 2001). In September 2000, the United Nations adopted the Millennium Development Goals, demonstrating its commitment to alleviating poverty. Moreover, the World Bank, the International Monetary Fund, governments, and non-governmental organisations have developed strategies to reduce poverty, particularly in EMDEs (Nsiah & Tweneboah, 2024).

4.3.2 Poverty reduction challenges in EMDEs

Poverty reduction in EMDEs remains a challenge that requires a holistic strategy. To address this challenge, some considerations and efforts should be made toward fostering inclusive growth, investing in quality education, increasing job creation, and adopting and using innovative technologies, amongst others. Measuring poverty is important for assessing its reach and impact. There are various methods for measuring poverty. These methods include the following:

a) *Poverty Lines*

These can be in the form of either absolute or relative poverty lines. Absolute poverty lines determine individuals who live below a predetermined, arbitrary standard of living. For instance, the current global poverty line, as determined by the World Bank, is $2.15 per person per day. This global poverty line was updated in September 2022, replacing the $1.90 poverty line. The relative poverty line, on the other hand, quantifies or measures poverty for the societal well-being of individuals (Arndt et al., 2017).

b) *Multi-Dimensional Poverty Index (MPI)*

Existing literature broadly indicates that poverty is multidimensional (Alkire et al., 2022; Atkinson, 2019; World Bank, 2018). The MPI records the extreme multidimensional poverty in EMDEs. Furthermore, the MPI has been published in the Human Development Report every

year since 2010. The index was developed by Alkire and Santos (2014) jointly with the United Development Program for the 2010 Human Development Report. The main objective of the index is to provide a clear, disaggregated, and, to the greatest degree feasible, comparable assessment of severe multidimensional poverty across more than 100 developing countries (Alkire et al., 2022). The MPI measures poverty by employing three dimensions, namely, health, education, and standard of living. These dimensions resemble the Human Development Index (HDI). The main difference between the HDI and the MPI is that the former uses aggregate-level data, while the latter employs individual-level data.

c) *Poverty Headcount Ratio (H-Measure):*

The Poverty Headcount Ratio measures the proportion of individuals who live below a certain poverty line. The headcount ratio is the main indicator used in the Sustainable Development Goals (SDGs) to measure financial and multidimensional poverty (Alkire et al., 2021). Further, the headcount ratio is the most straightforward and frequently employed measure of poverty. Due to its simplicity, the headcount ratio can provide a quick evaluation of levels of poverty across various countries, hence, it is mostly employed by global organisations such as the World Bank, governments, and non-governmental organisations.

d) *Income and Expenditure*

Poverty can also be measured by using the average income or expenditure of individuals (Deaton, 2006). To determine the extent of poverty and its composition, measures for income and expenditure are often employed to establish poverty lines that reflect the availability of financial resources and the standard of living (Saunders et al., 2002). Household consumption expenditure typically results in a measurement that is more accurate relative to the income approach (Brewer et al., 2017). The benefit of expenditure over income can be attributed to the fact that household expenditure questions tend to be less sensitive than income questions in a survey (Ali, 2019). It is for this reason that this study opts to use household consumption expenditure as a measure of poverty.

4.3.3 The Concept and Measurement of Inclusive Growth

Currently, there is no consensus amongst scholars on how to define inclusive growth. For instance, Grömling and Klös (2019) state that inclusive growth entails creating opportunities and providing access to a wider range of economic activities. Ranieri and Ramos (2013) define inclusive growth as growth that benefits everyone while decreasing the disadvantages encountered by the most underprivileged. Global organisations lack a universal definition of inclusive growth. Samans et al., (2015) of the World Economic Forum define inclusive growth as output growth that is long-term, widespread across economic sectors, creates opportunities for most of the working-age population in a country to find productive employment, and lowers the rate of poverty. According to the World Bank (2013), inclusive growth is the pace and distribution of economic growth.

Economic growth on its own is not sufficient to accomplish equitable growth. International discussions have acknowledged that developing countries should strive to achieve inclusive growth as it goes beyond the concept of economic growth (Kouton, 2019). Inclusive growth is rapidly growing traction (Cavanaugh & Breau, 2018) and seeks to promote an integrated approach to growth that considers several factors, including, income inequality reduction, fair and sustainable job opportunities for all, poverty alleviation, access to healthcare, clean water, access to education, and overall elevated standards of living. The United Nations Development Programme ([UNDP], 2017) asserts that inclusive growth is the prosperity that is shared by all because of economic growth or equity with growth. Key determinants of inclusive growth such as robust institutions, the creation of satisfactory jobs, social security, and investment in human capital can be identified in the definitions provided above.

It can be challenging to reduce inclusive growth to a concept that can be measured easily as it is a multifaceted concept. Various definitions, data sources, methodologies, and indicators have been used to measure inclusive growth (Barnat et al., 2023). Income from employment is one potential conduit through which people can benefit from economic growth (Kouton, 2019). Various studies have used GDP per person employed (constant 2017 Purchasing Power Parity $) as a proxy for inclusive growth (Adeniyi et al., 2021; Kouton, 2019; Olanrewaju et al., 2020; Raheem et al., 2018). GDP per person employed accounts for the income per worker as opposed to income per person in the population.

Put differently, this measure is centred around the individuals involved in the production process (Adeniyi et al., 2021). Raheem et al. (2018) justify using GDP per person employed as a proxy for inclusive growth as it considers both the distribution of opportunities throughout the population and the average opportunities that are available in the population. Another justification for the use of GDP per person employed as a proxy is that inclusive growth relies on the creation of good and sustainable jobs (Kouton, 2019). Based on the foregoing, the present study used GDP per person employed (constant 2017 Purchasing Power Parity $) as a proxy for inclusive growth.

4.2.3 Theoretical Literature

The theory of Financial Intermediation underpins this study (Goldsmith, 1969; McKinnon, 1973; Shaw, 1973). Financial intermediation is simply a process whereby financial institutions (such as mutual funds, banks, pension funds, and insurance companies) channel funds between those who save (depositors) and those who invest (investors) (Gorton & Winton, 2002). The agency theory and the theory of information asymmetry form the foundation of the financial intermediation theory (Andrieş, 2009). High transaction costs, regulation methods, and incomplete information are some of the factors that explain why financial intermediaries exist. Nonetheless, information asymmetry is the leading and most used approach in existing literature regarding financial intermediation theory. The information of asymmetry concept is whereby parties in a transaction have unequal amounts of information, which may result in problems such as adverse selection and moral hazard. By operating as designated supervisors and providing information to market participants, financial intermediaries can solve the issue of information asymmetry (Diamond, 1984; Leland & Pyle, 1977).

Financial intermediation is also based on the transaction costs approach established by Fama (1980) and Benston and Smith (1976), which deals with the variations of technology each participant uses (Andrieş, 2009). Financial intermediaries can assist in reducing transaction costs by aggregating the savings of several savers and lending them to investors (Levine, 1998). By so doing, financial intermediaries can spread the cost of locating borrowers and upholding a greater number of transactions. Moreover, financial intermediaries are essential in fostering inclusive growth in EMDEs, especially since financial markets in these regions are often underdeveloped. Financial intermediaries allocate capital effectively and promote investments, thus serving in the capacity of a conduit between those who save and those who borrow.

The study's third objective investigated the effect of digital financial inclusion on inclusive growth and poverty in EMDEs. The theory of financial intermediation is thus linked to this objective as high transaction costs discourage individuals from participating in the formal financial sector, ultimately resulting in high financial exclusion, high poverty levels, and low inclusive growth. Moreover, when market information is not shared equally, this tends to discourage individuals from participating in the financial market, increasing financial exclusion. On the other hand, lower transaction costs tend to increase digital financial inclusion, reduce poverty levels, and increase inclusive growth. Furthermore, when financial institutions are well-regulated and less risky, it encourages households to participate in the financial sector. Therefore, this makes the theory of financial intermediation suitable for this objective.

4.4 Review of Empirical Literature

Several studies have observed the relationship between either digital financial inclusion and inclusive growth or digital financial inclusion and poverty using different methodologies, data, and regions in the existing literature. Therefore, this section divides the empirical literature into studies that have examined 1) digital financial inclusion and poverty and 2) digital financial inclusion and inclusive growth.

4.4.1 Digital Financial Inclusion and Poverty

The effect of financial inclusion on poverty and vulnerability to poverty of Ghanaian households was studied by Koomson et al. (2020). A financial inclusion index was constructed using data from the Ghana Living Standards Survey's seventh round in 2016-17, and the vulnerability of families to poverty was estimated using a three-stage feasible least squares method and a multiple correspondence analysis. The study discovered that household poverty is affected by an increase in financial inclusion in two ways. First, it is associated with a 27% decrease in the chance of poverty in a home. Secondly, it shields a household from future poverty by 28%.

Kelikume (2021) investigated the nexus between poverty reduction, financial inclusion, mobile phones, the informal economy, and the internet. The system-GMM technique and a panel data set spanning 1995 to 2017 from 42 countries were employed in the study. The findings revealed a positive and significant relationship between the usage of the internet, mobile penetration,

and poverty alleviation. Moreover, the study found that an increase in financial inclusion leads to a reduction in poverty.

Using a two-step system GMM, Toda causality test, and simultaneous-equations models, Wale-Awe and Evans (2023) examined the causal relationship between the growth-poverty-inequality triangle and digital financial inclusion from 1995 to 2018 in 42 African countries. The cited study found that an increase in digital financial inclusion leads to poverty alleviation and inequality reduction. The findings also revealed a bi-causality between digital financial inclusion and poverty. Therefore, Wale-Awe and Evans (2023) suggest that enhancing access to digital financial services throughout the African continent is crucial to improving income levels, reducing poverty, and fostering an equitable income distribution.

Focusing on South Asia and Sub-Saharan Africa, Lyons et al. (2020) examined the association between financial and digital inclusion and poverty across seven developing countries. The cited study discovered that considerable decreases in poverty levels are associated with increases in several measures of financial and digital inclusion. The study underscores the significance of digital financial services in assisting and maintaining efforts to reduce poverty in developing countries.

China's efforts to reduce poverty are greatly impacted by digital financial inclusion. To that end, Lee et al. (2023) investigated the relationship between digital financial inclusion and reduction using Chinese provinces from 2011 to 2019. The findings indicate that poverty can be substantially decreased through digital financial inclusion. Using the spatial Dubin model, the study further found that the inclusion of digital financial services leads to a spillover effect that improves poverty alleviation.

Using the system-GMM and panel data spanning from 2011 to 2020 from 31 provinces, autonomous regions, and municipalities, Xie (2023) examined the dynamic relationship between increasing levels of digital financial inclusion and regional poverty. The cited authors concluded that digital financial inclusion can significantly lower poverty rates in China. Wang and He (2020) were one of the first attempts to investigate the effect of digital financial inclusion on poverty from a farmers' perspective. The study analysed survey data from 1900 rural households using the Asset-Based Vulnerability approach. The study found that the usage of digital financial services by farmers has a positive impact on lowering their vulnerability to poverty.

In China, Peng and Mao (2022) investigated the impact of digital financial inclusion on urban households' relative levels of poverty. The probit model, the mediating effect model, and the instrumental variable approach were used to perform empirical research. According to the findings, digital financial inclusion lowers the likelihood that urban households will experience poverty. Moreover, the study discovered that digital financial inclusion increases urban families' engagement in the financial sector and encourages entrepreneurship.

A study by Tay et al. (2022) yielded mixed results. Using a systematic literature review, the cited authors examined digital financial inclusion across countries. The study revealed that to combat poverty, developing countries, mostly those in Asia, embrace and enhance digital financial inclusion. However, the findings also showed that in terms of access to and use of digital financial services, disparity persists between gender, the wealthy and the poor, as well as between urban and rural areas in developing countries.

4.4.2 Digital Financial Inclusion and Inclusive Growth

In Sub-Saharan Africa, Sarpong and Nketiah-Amponsah (2022) employed the system-GMM estimation technique to empirically investigate the relationship between financial inclusion and inclusive growth. The study used a panel dataset of 46 countries spanning 2004 to 2018. The results indicate that when compared to other factors, financial services have a measurable and significant impact on inclusive growth. There is an improvement of 0.03 units in inclusive growth whenever there is an increase in the usage of financial services.

Based on the Auto-Regressive Distributed Lag (ARDL) model, Afolabi (2020) examined how financial inclusion impacts inclusive growth in Nigeria. The study used an annual series dataset encompassing the periods from 1981 to 2017. The results show that financial inclusion has a positive and significant impact on inclusive growth in the short and long run.

Using a two-step system-GMM, Iddrisu et al. (2023) explored the relationship between inclusive growth, financial stability, and financial inclusion in 40 African countries. The study period was from 2004 to 2020. Three findings revealed that financial inclusion fosters inclusive growth, and financial stability alone is not sufficient to promote inclusive growth. The study highlights that to increase inclusive growth, financial stability and financial inclusion must work together.

To establish whether digital financial inclusion promotes inclusive growth in China, Xun et al. (2020) compared the data from the China Family Panel Studies (CFPS), which provides representative household survey data in China, with the index of digital financial inclusion, which assesses the progress of digital finance in China. The authors found that digital finance increases household income in China, particularly in rural areas. As a result, digital finance helps China's inclusive growth by closing regional and urban-rural gaps. By distributing capital efficiently, decreasing information asymmetry and reducing risk, financial intermediation can contribute to increasing financial services access and fostering economic growth for underprivileged groups.

Wang and Yu (2024) investigated the impact of digital financial inclusion on inclusive growth, considering regional differences and transmission mechanisms. The study used a panel dataset comprising 31 provinces from 2011 to 2021. The study employed fixed effects and mediating effects estimation techniques to assess the relationship between digital financial inclusion and inclusive growth. The results of the study reveal that digital financial inclusion has a significant impact on growth in China, particularly in the eastern, western, and central regions. Furthermore, the study found that by facilitating the diffusion of innovation, digital financial inclusion can foster inclusive growth. The researchers concluded that China's inclusive growth will be supported by the establishment of digital financial inclusion.

Yang et al. (2024) investigated the influence of digital financial inclusion on inclusive growth. The study used a panel dataset of 30 provinces in China covering a period from 2011 to 2021. The entropy weight method of the fixed-base range was used as an estimation technique for the study. The results indicate that inclusive growth is significantly influenced by digital financial inclusion. Further, the study found that inclusive growth can be achieved through digital financial inclusion by enhancing and increasing innovation and the human capital level.

4.4.3 Summary of the Empirical Review Findings

Financial inclusion is viewed as one of the key components to improving inclusive growth and reducing poverty in developing countries (Khan et al., 2020). Furthermore, financial inclusion is regarded as a strong basis for any country's financial infrastructure (Liagat et al., 2022). Most studies have demonstrated that digital finance does reduce poverty and is closely related to the advancement and expansion of inclusive economic growth. Furthermore, research has revealed that a potent instrument for combating poverty is financial inclusion, particularly in EMDEs.

However, the existing literature does not explicitly contain studies examining the effect of digital financial inclusion on both inclusive growth and poverty. It is essential to examine how digital financial inclusion impacts poverty and inclusive growth since these two topics are closely connected and important for equitable growth. Given how closely related inclusive growth and poverty are and how they are highly influential on each other, it is essential to investigate how digital financial inclusion affects both simultaneously, especially in EMDEs.

Notably, the simultaneous assessment of the impact of digital financial inclusion on both inclusive growth and poverty remains under-researched, hence the rationale for this study. Put differently, the effect of digital financial inclusion on poverty through the intervention of inclusive growth is not available in the existing literature. Therefore, there is a need to investigate the effect of digital financial inclusion on poverty through the intervention of inclusive growth. Unlike economic growth, inclusive growth ensures that the benefits of the growth of the economy are allocated equitably, thus reducing poverty.

4.5 Methodology

4.5.1 Theoretical Framework and Hypotheses

This section outlines the data employed and where it was obtained. It presents a summary of the research techniques and different variables used for the study's analysis. This section is divided into four parts: data selection and sources, model specification, measurement of the model, and estimation techniques.

The first step of the investigation was to minimise the dimensions of the data using the principal component analysis (PCA) approach. This study contributes to the literature by using dynamic panel methods in the analysis. Dynamic panel methods can produce effective estimators even when heteroscedasticity is present and serial correlation and endogeneity are corrected. Considering that the current study used dynamic panel data to estimate the effect of digital financial inclusion on inclusive growth and poverty in EMDEs, the System-Generalized Method of Moments (GMM) is employed as the main technique. Moreover, for purposes of robustness checks and comparison, this study employs difference-GMM as an alternative estimation technique.

This study's analytical techniques aim to test the following hypotheses empirically:

a) *First Hypothesis*

H_0: Digital financial inclusion has no significant effect on inclusive growth in emerging and developing economies.

H_1: Digital financial inclusion has a positive and significant effect on inclusive growth in emerging and developing economies.

b) *Second Hypothesis*

H_0: Inclusive growth has no significant effect on poverty in emerging and developing economies.

H_1: Inclusive growth has a negative and significant effect on poverty in emerging and developing economies.

4.5.2 Data Selection and Sources

This study was quantitative and used data generated from secondary sources. This study used panel data from 2013 to 2022 in 21 EMDEs due to the availability of data in these regions during this period. Given the prevalence of financial exclusion in EMDEs, research is essential in the region. The study period was selected due to the data availability for the chosen variables in EMDEs. Moreover, the starting year of this research was 2013 as some EMDEs chosen for this study did not have available data before 2013.

Table 4. 1: Sample Description

Region	No. of Countries in the Region
Central Africa	2
Southern Africa	4
West Africa	10
Oceania	2
South Asia	2
SouthEastern Europe	1
Total number of countries included in the sample	**21**

Source: Compiled by author

The following data sources were used: the Financial Access Survey of the IMF (FAS-IMF), and the World Development Indicators (WDI). The data spans 2013 to 2022. The FAS is a supply-side dataset on access to and use of financial products and services that was introduced in 2009 to help policymakers evaluate and monitor financial inclusion and compare progress to peers. The WDI represents the World Bank's main collection of development indicators, collated from various reputable and reliable international sources. It offers the most recent and reliable global data.

4.6 Data Selection, Description, and Measurement of Variables

Data were selected based on the various dimensions and indicators that the study used.

4.6.1 Dependent variable (s):

a) *Inclusive Growth*

This study used GDP per person as a proxy for inclusive growth. GDP per person employed (constant 2017 Purchasing Power Parity $) has been employed as a proxy for inclusive growth in several studies (Adeniyi et al., 2021; Kouton, 2019; Olanrewaju et al., 2020; Raheem et al., 2018). The focus of this measure is the people who work in the production process. Inclusive growth ensures that the growth of the economy is distributed equitably. Further information on inclusive growth is presented in section 4.2.2.

b) *Poverty*

The presented study employed household consumption expenditure as a proxy for poverty levels of the selected countries due to the lack of poverty data in these countries. Household consumption expenditure has been validated by Akanksha and Odhiambo (2010) and, more recently, by Musakwa and Ohdiambo (2021). The cited studies employed household consumption expenditure to reflect the income aspect of poverty. Quartey (2008) attests that household consumption expenditure data amongst the impoverished is typically more frequently and accurately reported than income data. Moreover, Nyasha et al. (2017) also justify using household consumption expenditure as a proxy for poverty as it is found to be a reliable variable. Existing literature has used household consumption expenditure as a proxy for poverty (Dhrifi, 2015; Kaidi et al., 2019; Musakwa & Odhiambo, 2019; Nsiah & Tweneboah, 2024; Quartey, 2005;). Data on household consumption expenditure were

collected through a single cross-section survey for an adequately representative sample of the selected countries, employing households as the unit of observation.

Finally, following standard practice in econometric analysis to address skewness and to interpret coefficients in percentage terms (elasticities), the variable is transformed into its natural logarithmic form for use in the regression models. Therefore, the variable POV in our empirical models represents the log of real household consumption expenditure per capita, where a decrease in this value indicates a deterioration in living standards and an increase in poverty.

4.6.2 Explanatory Variables: Digital Financial Inclusion

The following dimensions and indicators were used to measure digital financial inclusion.

a) *Access (Penetration of Basic Financial Services)*

Mobile money agent outlets active (per 100,000 adults) and mobile money agent outlets active (per 1,000 km^2) serve as indicators of the access dimension as part of the geographic or demographic penetration (Banna, 2020). These indicators are important and necessary for the internet, mobile money, and mobile banking to be used as new avenues for accessing financial services. Moreover, in several markets, the availability of mobile money agents in remote areas has significantly increased access to financial services (Khera et al., 2021). Data for these indicators was sourced from the FAS-IMF.

b) *Usage*

For the usage dimension, the number of active mobile money accounts (per 1,000 adults), number of mobile and internet banking transactions (during the reference year) per 1,000 adults, and value of mobile and internet banking transactions (during the reference year) (% of GDP) as indicators (Banik & Roy, 2023; Banna, 2020). Data for these indicators was sourced from the FAS-IMF. Digital financial inclusion can reach more households, thus providing financial access to individuals who were previously financially excluded, and this ultimately promotes inclusiveness.

c) *Age dependency Ratio*

The World Bank (2020) defines the age dependency ratio as a measurement of the proportion of dependents (both children and elderly individuals) to the working age group (from 15 to 64 years). A country's economy can be strained if many people cannot work due to age restrictions. This is because people who qualify to work would have to support the people who cannot work because of their age through taxes and other government programs. Vijayakumar (2013) established that most EMDEs, particularly those in Asia, Africa, and Latin America have challenges with unemployment, poverty, high age dependency ratio, and weak and unstable GDP growth. Applying inclusive growth strategies and implementing innovative income distribution guidelines can alleviate poverty more quickly (Anyanwu et al., 2013). The age dependency ratio is, therefore, expected to have a positive relationship with poverty.

d) *Gross National Income (GNI) per capita*

Gross National Income (GNI) per capita is calculated by dividing the gross national income of a country by its mid-year population. GNI per capita is a helpful measure to use when evaluating the development and progress of a country's economy. Higher GNI per capita countries typically have more resources at their disposal, which can be employed to better the lives of the impoverished. Khan et al. (2024 found that digital financial inclusion positively and significantly affects GNI per capita, thus suggesting that increasing access to digital financial services and products can improve the development of the economy. Therefore, GNI per capita is expected to have a positive relationship with digital financial inclusion.

e) *Education*

The gross enrolment ratio in primary education is used as a measure to determine the proportion of children who are of primary school age and are enrolled in primary school as a proportion of the corresponding age group (World Bank, 2022). Financial education aims to facilitate access to formal financial services and products, thus reducing financial exclusion (Grohmann & Menkhoff, 2021). EMDEs can elevate the livelihoods of their populations and end the poverty cycle through substantial investments in education. The preceding statement is supported by Hidalgo-Hidalgo and Iturbe-Ormaetxe (2018), who established that higher government spending on primary and secondary education is linked to reduced adult poverty rates. Furthermore, education is an essential component of inclusive growth (Adeniyi et al.,

2021). The World Economic Forum (2014) reported that creating inclusive and development-oriented growth requires both education and high-quality jobs. Therefore, we expect that an improvement in the level of education will have a positive relation with inclusive growth and an inverse relationship with poverty.

f) *Inflation*

Inflation is the gradual overall increase in the price level of goods and services that reduces purchasing power within an economy (Lim & Sek, 2015). It is used as a measurement of how much the price of a set of products and services has increased over a specific period, typically a year (IMF, 2023). The consumer price index (CPI) calculates the percentage change in the cost of a basket of goods and services that households consume. The CPI is the most widely used measure of inflation. Inflation is considered an influential component in determining the poverty rate (Masron & Subramaniam, 2018). High inflation makes it more challenging for poor households to improve their standard of living. Concerning how inflation influences inclusive growth, Pham et al. (2024) found that inflation impacts inclusive growth positively. Therefore, an inverse relationship is expected.

g) *General Government Final Consumption Expenditure (% of GDP) (GOVEXP)*

General government final consumption expenditure (% of GDP) encompasses current expenditures for all governments for buying goods and services. Government expenditures have a crucial role in promoting economic growth and the well-being of its citizens (Simatupang, 2020). Government expenditure is typically split into current expenditure and capital expenditure. Current expenditure pertains to the everyday operating expenses of the government. These costs include wages, salaries, supplies, etc. On the other hand, capital expenditure is defined as spending on assets that are typically long-term and encompass infrastructure (for instance, schools, roads, bridges), machinery, and other expenditures that promote a country's economic growth and development (Akanbi, 2019, Poku et al., 2022). Government expenditure that is well allocated towards inclusive policies can be an effective means of alleviating poverty and stimulating economic growth and development in EMDEs. Empirical literature demonstrates that government expenditure positively impacts economic growth and the reduction of poverty. However, due to high levels of expenditure, most EMDEs are experiencing fiscal deficits (Mehmood & Sadiq, 2010).

h) *Broad money to GDP (Money Supply)*

Broad money to GDP reflects the amount of money supply to the economy itself. Money supply illustrates how liquid financial instruments are for a given economy (Anjande et al., 2022). Broad money includes demand deposits, other liquid assets, foreign currency deposits, and cash. Increased money supply could stimulate investment and growth in the economy. Thus, job opportunities could potentially arise, and incomes increase due to the growth of the economy. The growth of the economy and the alleviation of poverty are accordingly driven by the increase in income levels resulting from the creation of job opportunities (Goshit & Longduut, 2016).

i) *Population Growth*

Population growth is a measure reflecting population density or abundance trends, and it indicates whether density and abundance are growing, declining, or stable, as well as the rate at which they change (Sibly & Hone, 2002). According to a 2022 report from the United Nations, the global population has more than tripled since the mid-twentieth century. Moreover, the report states that in November 2022, the world's human population amounted to 8 billion and is expected to increase to 9.7 billion by 2050. Over the past few years, policymakers and researchers have advocated for more global growth that is inclusive (Tella & Alimi, 2016). Adeosun et al. (2020) and Sajid and Ali (2018) employed population growth as a control variable in their studies.

j) *Institutional Quality*

Institutional quality is one of the control variables in our study. Understanding institutions assists in clarifying why some countries are wealthy while others are not, as well as why some have a political system that enhances while others do not (Grief, 2006). Since institutions are multifaceted, defining institutional quality is challenging (Vasilyeva et al., 2018). Policymakers and academics debate the idea of governance frequently, however, currently, there is no consensus on how to define governance or institutional quality. A range of definitions has been provided by different scholars and organisations. For instance, Kaufmann et al. (2011) define governance as the traditions and institutions that govern how authority is exercised in a country. Olander (2019) defines it as following an impartiality standard.

More than 200 countries and territories are covered by the Worldwide Governance Indicators (WGI) project, which provides both aggregate and individual governance indicators encompassing six governance dimensions since 1996. These dimensions are Control of Corruption, Government Effectiveness, Political Stability and Absence of Violence/Terrorism, Regulatory Quality, Rule of Law, and Voice and Accountability. dimensions are commonly regarded as the most reliable and accurate measures of institutional quality (Rodríguez-Pose & Di Cataldo, 2015).

Tebaldi and Mohan (2010) argue that poverty levels are impacted by institutional quality through weak market conditions and resources that are not allocated appropriately. Institutions that foster market development are essential for both reducing poverty and promoting economic prosperity (Ravallion & Chen, 2003). Furthermore, Fagbemi et al. (2020) suggest that economic developments favourable to the poor could be amplified by an effective institutional framework.

k) *GDP Growth*

Economists generally agree that the most comprehensive indicator of a country's economic performance or growth is the gross domestic product (GDP) (Ashley & Sun, 2017). GDP assesses the monetary value of finished goods and services purchased by the end user, generated in a country within a particular duration, such as a year or quarter (International Monetary Fund, 2023). Economic growth is generally viewed in a positive light. Possible outcomes such as improved standards of living, more job opportunities, poverty reduction, and higher government tax revenue can all be accomplished through economic growth.

Table 4. 2: Summary of the Independent Variables' Prior Expectational Indications

Variable	Description	Expectation Indication	Data Source
DFI	Digital Financial Inclusion	Positive (+)	FAS-IMF
IG	Inclusive Growth	Negative (-)	WDI
POV	Poverty	Negative (-)	WDI
DCPS	Domestic credit to private sector by banks (% of GDP)	Positive (+)	WDI
DPR	Age Dependency Ratio		WDI
GNI	GNI per capita (constant 2015 US$)	Positive (+)	WDI
EDU	Education	Positive (+)	WDI
INF	Inflation	Positive (+)/ Negative (-)	WDI

GOVEXP	General government final consumption expenditure (% of GDP)	Positive (+)	WDI
BM	Broad money to GDP	Positive (+)	WDI
GDP Growth	Gross Domestic Product	Positive (+)	WDI
PG	Population growth (annual %)	Positive (+)	WDI
IQ	Institutional Quality	Positive (+)	WGI

Source: Author's expectations

4.6.3 Panel Unit Root Tests

Before commencing the estimation process, this study examines the stationarity of the data using the most recent and efficient panel unit roots and cointegration approaches. The present study adopted the Levin, Lin, and Chu (LLC) test and the Hadri test.

a) *LLC Unit Root Test*

The LLC unit root test is particularly designed for panel data. It is one of the most often used unit root tests in research. The purpose of the LLC is to assess the null hypothesis of a common unit root in the panel data against the alternative hypothesis of stationarity in the case where the cross-sectional units are independent of one another (Westerlund, 2006).

b) *Hadri Unit Root Test*

The null hypothesis of stationarity is the foundation for the test suggested by Hadri (2000). It is a development of the stationary test created in the context of time series by Kwiatkowski, Phillips, Schmidt, and Shin (1992), which considers two models: (1) stationary around a deterministic level and (2) stationary around a deterministic trend. Hadri suggests a residual-based Lagrange multiplier test for the null hypothesis that the individual series y_i:t (for i = 1…N) are stationary around a deterministic level or a deterministic trend, against the alternative of a unit root in panel data (Hurlin & Mignon, 2007).

4.6.4 Principal Component Analysis

Using the approach of Camara and Tuesta (2014) adopted by Khera et al. (2021) and Ismael and Ali (2021), this study employs a two-stage Principal Component Analysis (PCA) to construct a new financial inclusion index. Constructing a financial inclusion index for EMDEs allows for the assessment of these countries' progress over time. This offers the possibility of

comparing financial inclusion levels across countries. PCA is a useful technique to minimise information loss while reducing the number of variables that reflect the same concept (Datta and Singh, 2019).

The PCA technique can decrease data sets to smaller dimensions while retaining as much of the original data as possible. The PCA technique scientifically calculates the weights for each dimension instead of manually assigning them, and it also eliminates the correlated variables that do not contribute to any decision-making. Moreover, using a two-stage PCA reduces the likelihood of the PCA being skewed towards the weight of the indicators for a given dimension. The PCA method is demonstrated in what follows.

i) ***The first stage of PCA:*** *Estimate the dimensions (access and usage)*

This study uses indicators for access and usage dimensions (as per the approach of Khera et al., 2021). This essentially means that the two endogenous variables Y^a and Y^u are unobserved for each index and must be estimated using their corresponding parameters (τ and δ, in the equation below:

$$DFI_i = w_1 Y_i^a + w_2 Y_i^u + e_i \quad (4.1)$$

where DFI is the digital financial inclusion index of a country i

e_i is the variation due to error

$w_1, w_2,$ represent the weights of each dimension; and

Y_i^a, Y_i^u represent dimensions for access and usage. These dimensions are further computed as:

$$Y_i^a = \tau_1 \text{ Mobile Money Agent per 100000 Adults} + \tau_2 \text{ Mobile Money Agent per 1000 km}^2 + e_i \quad (4.2)$$

$$Y_i^u = \delta_1 \text{ Active Mobile Money} + \delta_2 \text{ No of Internet Banking Transactions} + \delta_3 \text{ Value of Internet Banking Transactions} + e_i \quad (4.3)$$

Significant differences exist between country-specific values of the various financial inclusion indicators. Therefore, to improve data comparability, the Min-Max approach is used to normalise the dataset. By subtracting the minimum value and dividing it by the range of the

indicators' values, this procedure puts all the distinct indicators within an equal range between 0 and 1(Le et al., 2019). The normalisation formula is presented in equation (5) below:

$$X_{i,d} = \frac{(x_i - m_i)}{(M_i - m_i)} \quad (4.4)$$

Where x_i indicates the value of indicator *i,* m_i is the minimum value of indicator *i* and M_i is the maximum value of dimension *i*. $X_{i,d}$ represents the standardised value of indicator *i* of dimension *d.*

The estimator of each dimension is represented by the following weighted averages.

$$Y_i^a = \frac{\sum_{j,k=1}^{p} \lambda_j^a PC_{ki}^a}{\sum_{j=1}^{p} \lambda_j^a} \quad (4.5)$$

$$Y_i^u = \frac{\sum_{j,k=1}^{p} \lambda_j^u PC_{ki}^u}{\sum_{j=1}^{p} \lambda_j^u} \quad (4.6)$$

The correlation matrix is defined as Rp (pxp) of the *p* standardised indicators for each dimension. λ_j (j =1,…,p) is described as the j^{th} eigenvalue of each of the dimensions. j represents the number of principal components (PC). The first PC accounts for the greatest degree of variation in the explanatory variables. γj(px1) is the eigenvector of the correlation matrix. The assumption made is that λ1 >λ2 >⋯>λp and represents where P_k (k=1,…,p) as the *k-th PC* (weights)

The second stage of PCA: After getting the dimension indices, another PCA is conducted to determine the weights for financial inclusion.

The overall financial inclusion index is computed by combining all the separate indices into equation (1) to estimate the parameter (λ), that is:

$$TFI_i = \frac{\sum_{j,k=1}^{p} \lambda_j PC_{ki}}{\sum_{j=1}^{p} \lambda_j} \quad (4.7)$$

PC_{ki} (which represents each component) is expressed as a linear combination of the three dimensions and their respective eigenvectors of the correlation matrices as follows:

$$PC_{1\epsilon} = \pi_{11} Y_i^a + \pi_{12} Y_i^u \quad (4.8)$$

$$PC_{2_i} = \pi_{21} Y_i^a + \pi_{22} Y_i^u \quad (4.9)$$

By replacing the PC_{ki} as written in equations (8) and (9), the financial inclusion index can therefore be expressed as

$$TFI_i = \frac{\sum_{j=1}^{3} \lambda_j (\pi_{j1} Y_i^a + \pi_{j2} Y_i^u)}{\sum_{j=1}^{3} \lambda_j} \quad (4.10)$$

Equation (10) can thus be written as a linear equation for the weighted average of the financial inclusion index:

$$DFI_i = w_1 Y_i^a + w_2 Y_i^u + e_i \quad (4.11)$$

The digital financial inclusion index is then used to classify the various countries into three groups.

$0.5 < DFI \leq 1$ illustrates high digital financial inclusion.

$0.3 \leq DFI < 0.5$ demonstrates medium digital financial inclusion.

$0 \leq DFI < 0.3$ shows low digital financial inclusion.

4.3.6 Panel Estimation Techniques: System-Generalized Method of Moments (GMM)

This study employed system-GMM to estimate the effect of digital financial inclusion on inclusive growth and poverty in EMDEs. Hansen (1982) was the first to introduce GMM approaches. Holtz-Eakin, Newey, and Rosen further refined them (1988), while Arellano and Bond (1991) advocated for the difference-GMM. The difference-GMM estimator is designed for data with numerous individuals but few periods, that is, small T and large N panels.

The system-GMM was then outlined by Arellano and Bover (1995) and extensively developed by Blundell and Bond (1998). The system-GMM formulates supplementary orthogonality conditions that make more valid instruments accessible and achieve efficiency gains. System GMM addresses heteroscedasticity problems, bias of omitted variables, endogeneity between variables, and autocorrelation (Ali et al., 2022). Employing the panel data technique enables the endogeneity of the model or regressors to be addressed while addressing several periods and individual effects (Labra Lillo & Torrecillas, 2018). Furthermore, dynamic panel methods can produce estimators even when heteroscedasticity is present and serial correlation and endogeneity are corrected.

This study used the system-GMM instead of the difference-GMM estimator as the system GMM offers reliable and effective estimates, solves the endogeneity issue, and better fits panel studies. Like difference-GMM, the system-GMM estimator is developed for data with many individuals but few periods, that is, small T and large N panels. The system GMM produces more accurate estimates with a minimal bias relative to the difference of GMM (Blundell and Bond, 1998).

This study's period is from 2013 to 2022, while the number of EMDEs used is 21, and the system GMM is suitable, as alluded to earlier that N>T to avoid large instruments. The study uses a panel compiled annually. Another way to evaluate whether the estimation technique should be static or dynamic is to check whether the dependent variable is lagged and whether it is part of the regressors. If it lags, then the suitable approach is dynamic (Gujarati, 2012). The System-GMM is demonstrated below:

a) *Model 1*

$$IG_{i,t} = \alpha_0 + \alpha_1 DFI_{it} + \alpha_2 X_{it} + \varepsilon_{i,t} \quad (4.12)$$

X_{it} is the vector of exogenous control variables and is expanded in equations (4.13) and (4.14).

Equations (4.13) and (4.14) represent the random and fixed effects, respectively, which are static models.

$$IG_{it} = \alpha_0 + \alpha_1 DFI_{it} + \alpha_2 INF_{it} + \alpha_3 PG_{it} + \alpha_4 GOVEXP_{it} + \alpha_5 GNI_{it} + \alpha_6 DPR_{it} + \alpha_7 IQI_{it} + u_{it} + \varepsilon_{it} \quad (4.13)$$

$$IG_{it} = \beta_i + \alpha_0 + \alpha_1 DFI_{it} + \alpha_2 INF_{it} + \alpha_3 PG_{it} + \alpha_4 GOVEXP_{it} + \alpha_5 GNI_{it} + \alpha_6 DPR_{it} + \alpha_7 IQI_{it} + u_{it} + \varepsilon_{it} \quad (4.14)$$

$$IG_{it} = IG_{it-1} + \alpha_0 + \alpha_1 DFI_{it} + \alpha_2 INF_{it} + \alpha_3 PG_{it} + \alpha_4 GOVEXP_{it} + \alpha_5 GNI_{it} + \alpha_6 DPR_{it} + \alpha_7 IQI_{it} + u_{it} + \varepsilon_{it} \quad (4.15)$$

where; IG_{it} represents inclusive growth, IG_{it-1} is the inclusive growth lag, α is the coefficient of the estimated equation, INF_{it} denotes the inflation, PG_{it} is the Population growth (annual

%), $GOVEXP_{it}$ is the government expenditure, GNI_{it} is GNI per capita, DPR_{it} is the age dependency ratio, and IQI_{it} is the institutional quality.

u_{it} is the fixed effect by country, $\varepsilon_{i,t}$ is the error term, *i* is the country index, and *t* is the period (years).

b) *Model 2*

$$POV_{i,t} = \beta_0 + \beta_1 DFI_{it} + \beta_2 X_{it} + \varepsilon_{i,t} \quad (4.16)$$

X_{it} is the vector of exogenous control variables and is expanded in equations (4.16) and (4.17).

Equations (4.17) and (4.18) represent the random and fixed effects, respectively, which are static models.

$$POV_{it} = \beta_0 + \beta_1 IG_{it} + \beta_2 INF_{it} + \beta_3 BM + \beta_4 IQI_{it} + \beta_5 GDPGROWTH_{it} + \beta_6 PG_{it} + \beta_7 DFI_{it} + u_{it} + \varepsilon_{it} \quad (4.17)$$

$$POV_{it} = \alpha_i + \beta_0 + \beta_1 IG_{it} + \beta_2 INF_{it} + \beta_3 BM + \beta_4 IQI_{it} + \beta_5 GDPGROWTH_{it} + \beta_6 PG_{it} + \beta_7 DFI_{it} + u_{it} + \varepsilon_{it} \quad (4.18)$$

$$POV_{it} = POV_{it-1} + \beta_0 + \beta_1 IG_{it} + \beta_2 INF_{it} + \beta_3 BM + \beta_4 IQI_{it} + \beta_5 GDPGROWTH_{it} + \beta_6 PG_{it} + \beta_7 DFI_{it} + u_{it} + \varepsilon_{it} \quad (4.19)$$

where; POV_{it} represents poverty, POV_{it-1} is the poverty lag, β is the coefficient of the estimated equation, IG_{it} represents inclusive growth, INF_{it} denotes the inflation, BM_{it} is the broad money to GDP, IQI_{it} is the institutional quality index, $GDPGROWTH_{it}$ is Gross Domestic Product growth, PG_{it} is the population growth, and DFI_{it} is digital financial inclusion.

u_{it} is the fixed effect by country, $\varepsilon_{i,t}$ is the error term, *i* is the country index, and *t* is the period (years).

4.6.5 Diagnostic Tests

This section outlines the diagnostic tests conducted to ensure the robustness and validity of the empirical model. Specifically, it presents the results of the Sargan/Hansen test for

overidentifying restrictions, the Arellano-Bond test for autocorrelation, and the Breusch-Pagan test for heteroskedasticity, each designed to assess different aspects of model integrity.

a) *Sargan/Hansen Test for Overidentifying Restrictions*

The traditional GMM test of overidentifying restrictions related to Sargan (1985) and Hansen (1982) is frequently used to assess the validity of the moment conditions provided by dynamic data models (Bowsher, 2000). The null hypothesis of the Sargan test is that the instruments are valid. In other words, there is no correlation between the instruments and the error term. On the other hand, the alternative hypothesis states that the instruments are not valid. This means there is no correlation between the error term and at least one of the instruments.

b) *Autocorrelation Test (Arellano-Bond Test)*

The residual correlation test is another test for dynamic panel estimation. In particular, the Arrellano-Bond test is widely used to determine if the dynamic panel data model residuals have or show autocorrelation. Autocorrelation also quantifies which variable is correlated with its lagged values. The null hypothesis of the Arellano-Bond autocorrelation tests of the first order (AR1) and second order (AR2) is that there is no autocorrelation in the residuals. The alternative hypothesis is that there is autocorrelation in the residuals.

c) *Heteroskedasticity Test*

To check for heteroskedasticity, the study used the Breusch-Pagan test. The null hypothesis states that residuals are homoscedastic. The alternative hypothesis states that heteroskedasticity exists.

4.7 Empirical Results and Discussion

This section presents the empirical findings of the study, beginning with descriptive statistics to characterise the data, followed by diagnostic tests including unit root and multicollinearity assessments, and culminating in an examination of pairwise correlations across the models employed.

4.7.1 Descriptive Statistics

Table 4.3, which follows, illustrates that digital financial inclusion has a mean value of 0.1305 and a standard deviation of 0.1023. Further, the minimum and maximum values are recorded at 0.0085 and 0.4831, respectively. The low average digital financial inclusion index demonstrates that digital financial inclusion is low in the EMDEs selected for this study. The 2021 World Bank report indicates that 1.4 billion adults around the globe are unbanked, and most of these individuals are based in EMDEs.

Table 4. 3: Summary Statistics for the Dataset

Variables	Observations	Mean	Standard deviation	Minimum	Maximum
DFII	210	0.1305	0.1023	0.0085	0.4831
IG	210	13699.22	12389.43	2874.83	52797.6
POV	210	23.8621	1.6841	20.4526	27.7492
DPR	210	76.2532	16.2236	40.4211	106.571
GNI	210	4935.125	5025.892	1133.455	24828.68
EDU	210	100.3608	16.1384	64.7559	137.6062
INF	210	7.976637	43.04846	-3.233389	55.2108
GOVEXP	210	15.7735	7.7227	5.1161	40.5535
TO	210	65.7311	26.3272	24.7016	146.4021
BM	210	41.3954	23.55757	14.3792	159.9491
PG	210	2.0917	0.9849144	-0.9269	3.8671
GDP Growth	210	4.0101	3.7310	-14.5465	11.8703
IQI	210	-0.0437	0.9989	-2.0477	2.6694

DFII: Digital Financial Inclusion Index; IG: Inclusive Growth; POV: Poverty; DPR: Age Dependency Ratio; GNI: GNI per capita (constant 2015 US$); EDU: Education; INF: Inflation; GOVEXP: General government final consumption expenditure (% of GDP); BM: Broad money to GDP; PG: Population growth (annual %); GDP growth: GDP Growth; IQI: Institutional Quality Index.

Source. Calculated by the author using Stata 18

Table 4.3 illustrates that digital financial inclusion has a mean value of 0.1305 and a standard deviation of 0.1023. Further, the minimum and maximum values are recorded at 0.0085 and 0.4831, respectively. The low average digital financial inclusion index demonstrates that digital financial inclusion is low in the EMDEs selected for this study. The 2021 World Bank report indicates that 1.4 billion adults around the globe are unbanked, and most of these individuals are based in EMDEs.

Individuals' living standards cannot be sustainably increased without inclusive growth (Naqvi, 2012). Our results in Table 4.2 above show that inclusive growth exhibits a mean value of

13699.22 and a standard deviation of 12389.43. The standard deviation suggests that many values differ significantly from the mean. This suggests that some countries from the sample have significantly high inclusive growth rates, while others have considerably lower inclusive growth rates. The variable has minimum and maximum values of 2874.83 and 52797.6, respectively.

The average poverty rate across the dataset is 23.8621, with a standard deviation of 1.6841. This suggests that, on average, approximately 24% of the population in the selected EMDEs is living below the poverty line. The standard deviation of 1.6841 indicates a relatively low level of variability in the poverty rates across the dataset. The minimum and maximum values are recorded at 20.4526 and 27.7492, respectively.

The age dependency ratio has a mean value of 76.2532 as a percentage of the working-age population and a standard deviation of 16.2236. The mean age dependency ratio of 76.25% suggests that for every 100 individuals in the working-age population, there are approximately 76 dependents. This indicates a significant level of dependency, which can place economic pressure on the working-age population to support the non-working segments of society. The standard deviation of 16.2236 indicates a moderate variability level in the age dependency ratios across the dataset. This variable also exhibits a minimum of 40.4211 and a maximum of 106.571.

The average Gross National Income (GNI) per capita is $4,935.13 with a standard deviation of $5025.89. The minimum value is recorded at $1,133.46 while the maximum value is at $24,828.68. Primary enrolment as a percentage of gross enrolment in education has a mean value of 100.3608 and a standard deviation of 16.1384, suggesting that most working-age people in EMDE are educated. The lowest education score is 64.7559 while the highest score is 137.6062.

Inflation shows a mean value of 7.9766 and a standard deviation of 43.0485. This suggests the dataset contains countries with very low or high inflation rates than the mean. The minimum value is recorded at -3.2334, whereas the maximum value is 55.2108. Government expenditure was found to have an average value of 15.7736 and a standard deviation of 7.7227, with a minimum value of 5.1161 and a maximum value of 40.5535. Trade (% of GDP) has a mean of 65.7312 and a standard deviation of 26.3272, illustrating a stable variable. Trade (% of GDP) exhibits a minimum value of 24.7016 and a maximum of 146.4021.

Broad money to GDP generated an average of 41.3954 and a standard deviation of 23.5576, meaning the selected EMDEs maintained a relatively balanced proportion of broad money to GDP with marginal changes over the period. The minimum and maximum values were recorded as 14.3793 and 159.9491, respectively. The annual population's average growth rate is 2.0917. The standard deviation of 0.9849 suggests that there has been considerable growth in the population in some of the selected countries, however, there has also been a reduction in the population growth rate in other countries from our dataset.

GDP growth has a mean value of 4.0101 percent, with a standard deviation of 3.7310. The minimum value is recorded at -14.5465, while the maximum is at 11.8703. Institutional quality has a mean value of -0.0437 and a standard deviation of 0.9989, with a minimum and maximum of -2.0478 and 2.6695, respectively. This indicates that this variable is not stable, thus showing variations. Unit Root Test Results are depicted below.

Table 4. 4: Unit Root Test Results for Digital Financial Inclusion Dataset

Variable	Levin-Lin-Chui		Hadri LM	
	Level		Level	
	Constant	Constant +Trend	Constant	Constant +Trend
DFII	-5.3821*** (0.0000)	-1.6054 ** (0.0542)	15.1448*** (0.0000)	1.4404 * (0.0749)
IG	-2.9160*** (0.0000)	-3.9809*** (0.0000)	15.1065*** (0.0000)	6.0057 **** (0.0000)
POV	-1.7285 ** (0.0420)	-6.2368*** (0.0000)	22.1750*** (0.0000)	1.3221* (0.0931)
DPR	9.2393 (1.0000)	-3.1925*** (0.0007)	22.4054*** (0.0000)	13.7787*** (0.0000)
IQI	-7.5343*** (0.0000)	-8.7303*** (0.0000)	8.6789*** (0.0000)	3.7162*** (0.0001)
INF	1.8300 (0.9664)	-4.0878*** (0.0000)	5.8073*** (0.0000)	-0.1282 (0.5510)
BM	-1.4876* (0.0684)	-4.9217*** (0.0000)	16.2548*** (0.0000)	2.0409** (0.0206)
GDP Growth	-5.8753*** (0.0000)	-8.6426 *** (0.0000)	-0.0757 (0.5302)	-0.0783 (0.5312)
EDU	-4.2329*** (0.0000)	-6.8878*** (0.0000)	15.9326*** (0.0000)	5.6781*** (0.0000)

GNI	7.2128 (1.0000)	9.8274 (1.0000)	3.6377*** (0.0001)	3.8019*** (0.0001)
PG	1.7091 (0.9563)	-3.1519*** (0.0008)	15.8107*** (0.0000)	10.9203*** (0.0000)
GOVEXP	-3.8951*** (0.0000)	-2.0130** (0.0221)	8.4703*** (0.0000)	3.1472*** (0.0008)

DFII: Digital Financial Inclusion Index; IG: Inclusive Growth; POV: Poverty; DPR: Age Dependency Ratio; IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); PG: Population growth (annual %); GOVEXP: General government final consumption expenditure (% of GDP).
****, *** denote the significance at the 1%, 5% and 10% levels respectively*
Note: () denote the p-values Source:
Calculated by the author in Stata 18

Table 4.4 above depicts the outcomes of the Levin-Lin-Chu and Hadri LM unit root tests for investigating the effect of digital financial inclusion on inclusive growth and poverty in EMDEs.

Both tests indicate that digital financial inclusion, inclusive growth, poverty, age dependency ratio, institutional quality, inflation, broad money to GDP, GDP growth, primary enrolment as a percentage of gross enrolment trade (% of GDP), Gross National Income (GNI), population growth, trade (% GDP), and government expenditure are all stationary at level [I (0)], indicating that they are valid, reliable and appropriate for the study, and thus will not generate spurious results.

Table 4. 5: Pesaran CIPS Unit Root Test Results for Cross-Sectionally Dependent Panels

Variable	CIPS Statistic	Critical Value at		
		10%	5%	1%
GNI	-2.379**	-2.12	-2.25	-2.51
BM	-2.232**	-2.12	-2.25	-2.51
PG	-2.482***	-2.1	-2.22	-2.44
TO	-2.768***	-2.12	-2.25	-2.51
IQI	-2.963***	-2.1	-2.22	-2.44
GOVEXP	-2.41**	-2.12	-2.25	-2.51
POV	-2.533***	-2.12	-2.25	-2.51
INF	-3.477***	-2.1	-2.22	-2.44
GDP Growth	-2.399**	-2.1	-2.22	-2.44
EDU	-2.316**	-2.12	-2.25	-2.51
DFII	-2.441**	-2.12	-2.25	-2.51
DCPS	-2.848***	-2.12	-2.25	-2.51
DPR	-2.736***	-2.1	-2.22	-2.44

DFII: Digital Financial Inclusion Index; IG: Inclusive Growth; POV: Poverty; DPR: Age Dependency Ratio; IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); PG: Population growth (annual %); GOVEXP: General government final consumption expenditure (% of GDP).

Note: The test includes an intercept. The lag length was selected automatically based on the Akaike Information Criterion (AIC). *, ** denote rejection of the null hypothesis of non-stationarity at the 1%, and 5% significance levels, respectively.**
Note: () denote the p-values Source:
Calculated by the author in Stata 18

As detailed in Table 4.5, the CIPS test statistics allow for the rejection of the null hypothesis of a unit root for all variables in the dataset. Specifically, seven variables, that is, DCPS, TO, IQI, INF, DPR, POV, and PG are stationary at the 1% significance level. The remaining six variables, that is, DFII, GDP Growth, GNI, GOVEXP, EDU, and BM are stationary at the 5% significance level.

The unambiguous conclusion from this robust second-generation test is that all series are integrated of order zero, I(0). This finding confirms the suitability of employing the variables in their level form for the subsequent System Generalized Method of Moments (GMM) estimation, thereby mitigating concerns regarding spurious regression and validating the empirical strategy undertaken in this chapter.

4.7.2 Multicollinearity – Variance Inflation Factor

The VIF was employed to test for multicollinearity. The results show that the independent variables' VIFs are less than 10, indicating no multicollinearity (see Table 4.6, which follows).

Table 4. 6: Variance Inflation Factor Test

Variable	VIF	1/VIF
GNI	6.14	0.162779
BM	5.16	0.193663
PG	4.46	0.224053
TO	3.7	0.270285
IQI	2.65	0.377376
GOVEXP	2.65	0.377597
POV	1.9	0.526329
INF	1.46	0.682774
GDP Growth	1.44	0.692971
EDU	1.42	0.703686
DFII	1.29	0.77326
Mean VIF	**2.94**	

MS: Broad money to GDP (Money Supply); IG: Inclusive Growth; PG: Population growth (annual %); IQI: Institutional Quality Index; POV: Poverty; EDU: Education; GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); INF: Inflation.

Source. Calculated by the author using Stata 18

4.7.3 Pairwise Correlation – Model 1

This section discusses the correlation between the dependent variable (inclusive growth) and each of the explanatory variables. The pairwise correlation matrix is presented in Table 4.7, which follows.

Table 4. 7: Pairwise Correlation Matrix for Model 1

	IG	DFII	INF	PG	GOVEXP	GNI	DPR	IQI
IG	1							
DFII	0.0252	1						
INF	-0.0679	0.3058	1					
PG	-0.6828	-0.0469	-0.018	1				
GOVEXP	0.089	-0.1334	-0.0917	-0.0305	1			
GNI	0.7313	0.039	-0.0633	-0.7203	0.0536	1		
DPR	-0.7436	-0.1882	0.0111	0.8972	-0.066	-0.7764	1	
IQI	0.7604	0.1404	-0.1366	-0.5104	0.0464	0.7423	-0.5465	1

Inclusive Growth; DFII: Digital Financial Inclusion Index; INF: Inflation; PG: Population growth (annual %); GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); DPR: Age dependency ratio; IQI: Institutional Quality Index.

Source: Author's computation

The correlation coefficient between inclusive growth and digital financial inclusion is 0.03, this indicates that there is a weak positive correlation between these two variables. Inflation is negatively correlated to inclusive growth. The correlation coefficient shows a weak negative correlation between inflation and inclusive growth. Population and inclusive growth have a moderate negative relationship with a correlation coefficient of -0.68. General government final consumption expenditure (% of GDP) correlates positively with inclusive growth. The correlation coefficient indicates a weak positive correlation between general government final consumption expenditure (% of GDP) and inclusive growth. GNI per capita is positively correlated to inclusive growth. Given that the correlation coefficient is higher than 0.7, there is a strong positive correlation between GNI per capita and inclusive growth. The Age dependency ratio and inclusive growth have a strong negative relationship, confirmed by a correlation of -0.74. coefficient. Institutional quality and inclusive growth have a strong positive relationship supported by a 0.76 correlation coefficient.

4.7.4 Pairwise Correlation – Model 2

The dependent variable (poverty) and each of the explanatory variables are discussed below. The pairwise correlation matrix is presented in Table 4.8 below.

Table 4. 8: Pairwise Correlation Matrix for Model 2

	POV	IG	DFII	INF	BM	IQI	GDP Growth	GOVEXP	PG
POV	1								
IG	-0.0205	1							
DFII	-0.0511	0.0252	1						
INF	-0.0075	-0.0679	0.3058	1					
BM	-0.1233	0.7555	-0.0069	-0.1269	1				
IQI	0.1236	0.7604	0.1404	-0.1366	0.5363	1			
GDP Growth	-0.1145	-0.0912	0.0132	-0.2505	-0.2248	-0.0656	1		
GOVEXP	-0.3373	0.089	-0.1334	-0.0917	-0.023	0.0464	-0.29	1	
PG	-0.1964	-0.6828	-0.0469	-0.018	-0.7869	-0.5104	0.2287	-0.0305	1

POV: Poverty; IG: Inclusive Growth; INF: Inflation; BM: Broad Money to GDP (Money Supply); IQI: Institutional Quality Index; GDP Growth: Gross Domestic Product growth; DFII: Digital Financial Inclusion Index; General government final consumption expenditure (% of GDP); PG: Population Growth.

Source: Author's Computation

Poverty and inclusive growth have a positive relationship. The correlation coefficient between poverty and inclusive growth is -0.02, indicating a weak negative correlation between these variables. Digital financial inclusion is negatively correlated with poverty. The coefficient of correlation of -0.05 reveals a weak negative relationship between digital financial inclusion and poverty. The relationship between inflation and poverty is weak and negative as confirmed by the correlation coefficient of -0.0075. Broad money supply to GDP is negatively correlated with poverty. The correlation coefficient shows a weak positive relationship between broad money supply GDP and poverty. A positive and weak relationship exists between institutional quality and poverty as indicated by the correlation coefficient of 0.12.

GDP growth is negatively correlated with poverty. The correlation coefficient of -0.11 indicates a weak positive relationship between GDP growth and poverty. General government final consumption expenditure (% of GDP) correlates negatively with poverty. The correlation coefficient indicates a weak negative relationship between the general government's final consumption expenditure (% of GDP) and poverty. There exists a weak negative relationship between population growth and poverty as demonstrated by the correlation coefficient of -0.19. Multicollinearity could be an issue if the zero-order (pairwise) correlation coefficient is strong between two regressors, particularly greater than 0.8 (Imdadullah et al., 2016). None of the variables in the two models above have a correlation coefficient greater than 0.8, indicating no multicollinearity.

Table 4. 9: Heteroskedasticity – Model 1

Test	Chi-squared (1)	Prob>chi-squared
Breusch-Pagan	0.36	0.5506

Source: Calculated by the author using Stata 18

Table 4. 10: Heteroskedasticity – Model 2

Test	Chi-squared (1)	Prob>chi-squared
Breusch-Pagan	2.20	0.1379

Source: Calculated by the author using Stata 18

The *p*-values of the Breusch-Pagan test for both model 1 and model 2 are greater than 5%, indicating no problem of heteroskedasticity in the data. In other words, the null hypothesis could not be rejected as there was insufficient evidence against it.

4.8 Estimated Results for Digital Financial Inclusion Index

Before computing the PCA test, it is necessary to run the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity. The KMO test is used to evaluate the suitability of the sample size for PCA whilst Bartlett's test of sphericity determines the intercorrelation of the indicators chosen for the study. PCA can be performed if KMO>=0.5 and X^2 (that is, Chi-square) in Bartlett's test of sphericity is statistically significant.

Table 4. 11: Kaiser–Meyer–Olkin Measure and Bartlett's Test of Sphericity

Test	Measure	Financial Inclusion dataset
Kaiser–Meyer–Olkin		0.651
Bartlett's test of sphericity	Chi-square	1896.806
	Degrees of freedom	78
	p-value	0.000

Source. Calculated by the author using Stata 18

Using STATA 18, a measuring model for constructing a financial inclusion index was carried out. The access (Y^a) and usage (Y^u) dimensions were used in the measurement model. To ensure the assessment scale is irrelevant, each dimension's indicators are standardised to have values ranging between 0 and 1 before the PCA is conducted, where 0 shows financial exclusion and 1 illustrates digital financial inclusion.

Table 4. 12: Principal Components Estimates for Sub-Indices

Component	Eigenvalue	Difference	Proportion	Cumulative
Access dimension				
Comp1 (Mobile money agent outlets active per 100,000 adults)	2.0447	0.8274	0.4089	0.4089
Comp2 (mobile money agent outlets active (per 1,000 km2)	1.2173	0.2934	0.2435	0.6524
Usage dimension				
Comp1 (number of active mobile money accounts per 1,000 adults)	0.9239	0.3279	0.1848	0.8372
Comp2 (number of mobile and internet banking transactions)	0.5959	0.3777	0.1192	0.9564
Comp3 (value of mobile and internet banking transactions)	0.2182	.	0.0436	1

Source. Calculated by the author using Stata 18

The results of the first-stage PCA are illustrated in Table 4.12 above. The eigenvalues of each sub-index and latent variables, access (Y^a) and usage (Y^u), are determined using the PCA method. Principal components with eigenvalues greater than one are the only ones considered for the analysis as the component with the highest eigenvalue retains more standardised variance (Kaiser, 1960; Nguyen, 2020). As per Table 4.10, the eigenvalues of the principal components for the two dimensions are as follows: 2.0447, 1.2173 (access); and 0.9239, 0.5959, 0.2182 (usage). Component 1 of the access and usage dimensions are the only principal components with eigenvalues of more than one. Therefore, the first component is the only one used for this study. Notably, the estimations of the dimensions are computed using weights allocated to the first component of each dimension.

Table 4. 13: Scoring Coefficients for Orthogonal Varimax Rotation (weights)

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Unexplained
Access dimension						
Mobile money agent outlets active per 100,000 adults	0.6459	-0.0666	0.0062	-0.2017	-0.7332	0
Mobile money agent outlets active (per 1,000 km2)	0.4328	-0.2605	0.5905	0.5771	0.2511	0
Usage dimension						
Number of active mobile money accounts per 1,000 adults)	0.6	0.1328	-0.2474	-0.4097	0.6271	0
Number of mobile and internet banking transactions	0.1715	0.7258	-0.3328	0.5723	-0.0751	0
Value of mobile and internet banking transactions	-0.0782	0.6191	0.6923	-0.3618	-0.0196	0

Source. Calculated by the author using Stata 18

The retrieved weights of each of the five indicators are displayed in Table 4.13 above. Considering this, for the access dimension, the weights assigned for the first component are 0.6459 for *mobile money agent outlet active per 100,000* indicators; and 0.4328 for *mobile money agent outlet active per 1,000km^2* indicator.

On the other hand, for the usage dimension, the *number of active mobile money accounts per 1,000 adults)* indicator has a higher weight at 0.60 relative to the *number of mobile and internet banking transactions* indicator *at 0.1715, and the Value of mobile and internet banking*

transactions at -0.0782. This illustrates that the *number of active mobile money accounts per 1,000 adults'*-indicator is more important than other indicators defining the usage dimension.

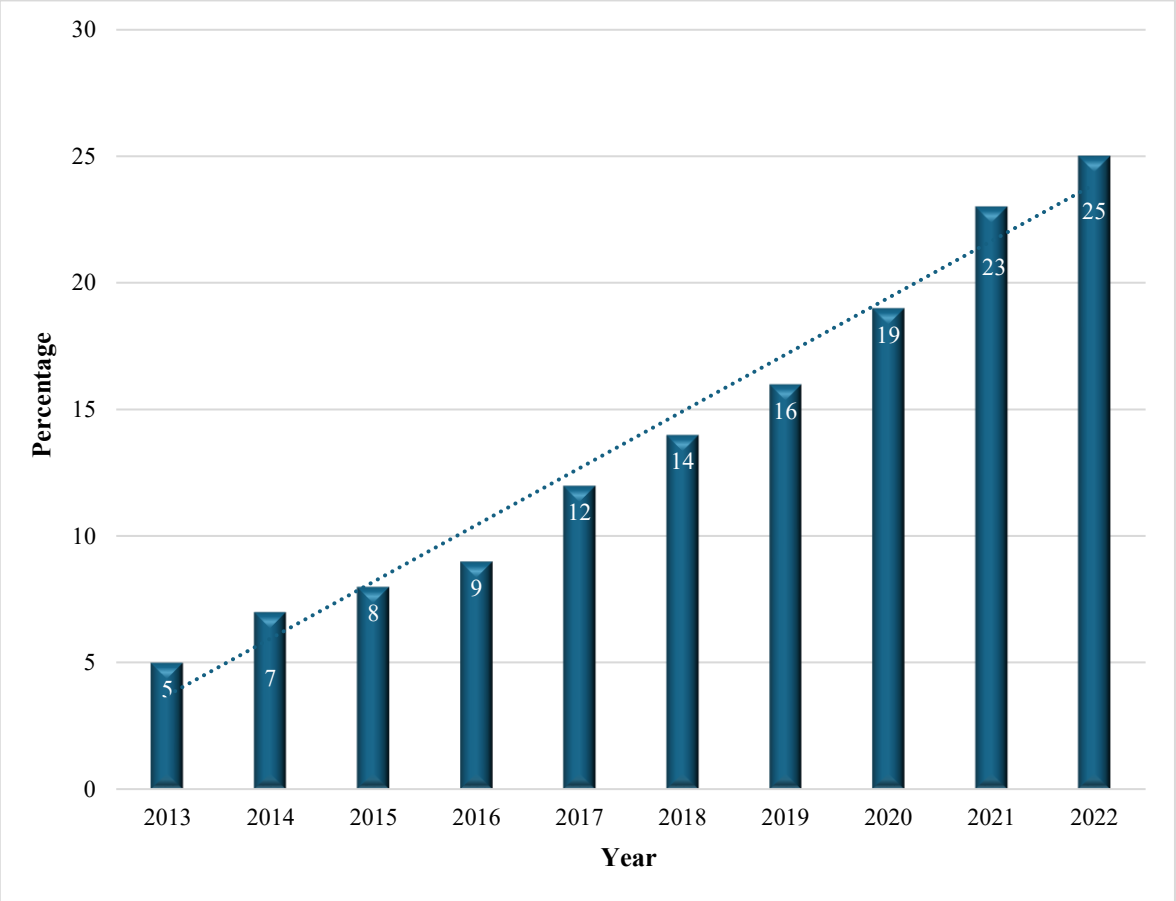
By allocating the weights retrieved above to equations [2] and [3] in section 4.3.5, equations [20] and [21] for access and usage dimensions are derived, respectively:

Y_i^a =0.6459 mobile money agent per 100,000 adults + 0.4328 mobile money agent per 100,000 km^2 + e_i [18]

Y_i^u =0.6active mobile money agent + 0.1715internet banking transactions - 0.0782value of mobile and internet banking transactions + e_i [19]

DFI = [0.6459mobile money agent per 100,000 adults + 0.4328 mobile money agent per 100,000 km^2] + [0.6 active mobile money agent + 0.1715 internet banking transactions - 0.0782value of mobile and internet banking transactions] + e_i [20]

Figure 4. 1: Average Digital Financial Inclusion Levels in EMDEs



Source. Calculated by the author

The digital financial inclusion index for EMDEs has been trending upward from 2013 to 2022, as indicated by Figure 4.1 above. This can be attributed to the growing importance of digital financial inclusion in EMDEs throughout the period under consideration.

Table 4. 14: Digital Financial Inclusion Values from 2013 – 2022

Country	Year											
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Mean	Average Digital Financial Inclusion
Albania	3.2060	3.7673	4.3303	4.8529	4.8245	4.9286	5.1125	5.3358	5.9467	4.701648	4.7005	Low
Bangladesh	9.9707	15.0300	15.3785	19.8796	24.7223	24.8288	23.5607	22.6790	27.0455	20.5864	20.3439	Low
Benin	0.8494	2.9981	5.1419	7.2805	11.4782	15.6542	22.5390	32.7740	35.4537	15.5467	14.9077	Low
Botswana	6.2219	8.0719	8.4420	9.6677	10.6670	11.5701	16.8367	20.0612	27.2104	13.3995	13.1943	Low
Burkina Faso	3.8692	4.5883	5.3038	6.0159	8.5670	13.8312	16.6375	18.4882	24.1452	11.2842	11.2718	Low
Cameroon	4.4849	4.9001	5.8310	5.1802	8.4463	10.3157	13.3597	16.4472	19.5014	9.8534	9.8296	Low
Côte d'Ivoire	5.5998	6.4342	7.2682	8.1018	13.3050	17.2933	22.3377	26.7631	33.8144	15.8022	15.6575	Low
Ghana	4.8008	6.3855	10.2873	15.7032	20.0115	22.6481	25.9437	32.8342	37.9060	20.1939	19.6134	Low
Guinea	1.0678	2.4680	4.0160	5.9474	7.6022	9.8666	12.5634	15.3101	18.0593	8.6240	8.5445	Low
Guinea-Bissau	3.8080	3.7914	3.7748	3.7579	4.6934	5.8833	10.8426	19.4031	21.8510	8.6581	8.6451	Low
Lesotho	4.5769	5.9448	7.6839	8.8344	11.5817	12.5667	14.9574	17.4736	23.9607	11.9603	11.9533	Low
Mali	5.7388	6.5825	7.4233	8.2610	8.2056	9.2503	10.4132	13.1505	14.4518	9.2935	9.2752	Low
Mauritius	9.1510	10.6535	12.1267	13.5691	14.9791	15.4519	20.1929	24.4382	29.2697	16.7738	16.6480	Low
Niger	5.1307	4.9598	4.7886	4.6172	4.5537	4.3490	4.1043	4.0635	4.8191	4.5989	4.5984	Low
Rwanda	8.8186	16.4191	18.0736	23.0219	26.9647	31.9171	33.4590	36.8927	37.6738	27.2445	25.9156	Low
Samoa	4.2813	4.4098	6.0485	5.9946	5.9652	5.6759	6.3065	6.1009	4.6202	5.4942	5.4892	Low
Senegal	7.2637	7.3549	7.4460	7.5370	9.8203	13.2728	18.1538	18.1981	43.3444	14.9484	14.7101	Low
Solomon Islands	3.7168	4.1616	4.2407	5.1401	4.9815	4.9798	4.5369	4.7433	4.9480	4.6064	4.6054	Low
Togo	3.2992	4.1134	4.9276	5.7418	8.2559	8.9544	11.4438	14.1905	16.8488	8.6616	8.6417	Low
Zimbabwe	12.3864	14.4626	17.3870	17.1016	26.0552	37.0011	39.7925	37.6548	33.3810	27.0417	26.1358	Low
Pakistan	5.0915	5.9564	7.2041	7.0747	7.3707	7.1273	7.5609	8.5701	10.0347	7.3352	7.3323	Low

Source. Calculated by the author

With data spanning 2013 to 2022, Table 4.14 above shows the digital financial inclusion values based on equation (20) for the 21 selected EMDEs. In the analysis, none of the countries had a high level of digital financial inclusion according to the ranking systems developed by Camara and Tuesta (2014). Between 2018 and 2021, Zimbabwe and Rwanda exhibited moderate digital financial inclusion, while Ghana only demonstrated a medium level of digital financial inclusion in 2020 and 2021. All the selected EMDEs fall into the low-level category since their average level of digital financial inclusion from 2013 to 2021 is less than 30%.

4.8.1 System GMM Results – Model 1

This section demonstrates the regression results on the effect of digital financial inclusion on inclusive growth in EMDEs.

Table 4. 15: System-GMM and Difference-GMM Outcomes

	Model	
Variables	**System-GMM**	**Difference-GMM**
lnIG (-1)	0.7428***(0.1398)	0.7754*** (0.0845)
lnDFII	0.0227*(0.0128)	-0.00125392
INF	-0.0003***(0.0000)	-0.0001(0.0001)
PG	-0.0972***(0.0266)	-0.0698**(0.0001)
lnGOVEXP	-00630 (0.0491)	-0.1520(0.1026)
lnGNI	0.1621(0.1622)	0.2084 (0.2969)
lnDPR	0.3452 **(0.1543)	-1.2349 **(0.5498)
IQI	0.0286(0.0272)	-0.0285 (0.0322)
Intercept	-0.0000 (0.9428)	
	Diagnostics	
R-squared		
Autocorrelation- Arrelano-Bond test (AR2)	0.96 [0.336]	0.67 [0.502
Sargan's test of overidentifying restrictions	6.78 [0.452]	0.48 [0.786]
Hansen's test of overidentifying restrictions	4.83 [0.681]	0.93 [0.628]
Friedman's test of cross-sectional independence	17.810 [0.5999]	17.810 [0.5999]
Pesaran test of cross-sectional independence (at 5% significance level)	-0.137 [0.8911]	

IG: Inclusive Growth; DFII: Digital Financial Inclusion Index; INF: Inflation; PG: Population growth (annual %); GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); DPR: Age dependency ratio; IQI: Institutional Quality Index.

Note: Inclusive Growth is the dependent variable
The number of observations is 189
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*

() denote the robust standard errors
[] denote the probability values

Source: Calculated by the author in Stata 18

Table 4.15 illustrates the results of the various panel methods employed by the study. Although system GMM is the primary estimation technique in this study, a difference-GMM was estimated for comparison and robustness checks. There are seven explanatory variables employed in GMM estimation techniques – digital financial inclusion, inflation, population growth, general government final consumption expenditure (% of GDP), GNI per capita (constant 2015 US$), age dependency ratio, and institutional quality. Table 4.14 further shows that four (digital financial inclusion, inflation, population growth, and age dependency ratio) of the seven explanatory variables were significant. The coefficient values suggest that explanatory variables vary in the degree of impact.

Digital financial inclusion is not significant under the difference-GMM estimation technique. However, other control variables such as population growth and age dependency ratio, are significant at 10%. Nonetheless, the difference-GMM has weaker instruments relative to system GMM, making it unsuitable for the present study. This is because it is claimed that the first difference GMM exhibits finite sample bias when the lags of the dependent variable have a weak correlation with the dependent variables' first difference in the subsequent period (Blundell and Bond, 1998).

Therefore, the system GMM estimation technique is the basis for interpreting the findings. This is because the system-GMM estimation technique provides the best outcome relative to the difference-GMM. Additional orthogonality restrictions provided by system-GMM increase the efficiency and reliability of instruments. This study employed the xtabond2 as suggested by Roodman (2009).

The main explanatory variable (digital financial inclusion) is significant under the system-GMM estimation technique. On the main independent variable, findings reveal that digital financial inclusion has a positive and significant effect on inclusive growth in EMDEs at a 10% significance level. The sign and magnitude indicate that when digital financial inclusion increases by a percentage point, inclusive growth will increase by 0.7428 units. Digital financial inclusion is regarded as one of the crucial elements to accomplishing inclusive growth as the process and effort of developing a digital society continues to grow (Song et al., 2022).

Financially excluded individuals can have the opportunity to participate in the formal financial sector by gaining access to essential financial services and products through available digital financial platforms. The digital finance sector is anticipated to grow, with increased financial access and inclusion, and inclusive growth due to the development and sharing of information and data through the internet (Xun et al.,2020). A stronger economy includes more people emerging from this increased participation in the financial sector. The findings are consistent with those of Xun et al. (2020) and Yang et al. (2024), who established that digital financial inclusion has a positive, significant effect on inclusive growth in their respective studies.

Inflation as a control variable significantly and negatively affects inclusive growth in EMDEs at 1% significance level. This signifies that there is an inverse relationship between inflation and inclusive growth. Inclusive growth will decrease by 0.0003 for a percentage inflation increase. Inflation decreases the value of money. The purchasing power of the public is reduced by high and unsteady inflation, particularly individuals with occupations that pay poorly. Therefore, purchasing necessities may become difficult for individuals, hindering their ability to participate in the economy. Sajid and Ali (2018) argue that rising inflation makes it difficult for developing countries to achieve economic growth. The best monetary policies for inclusive growth are those geared toward maintaining low inflation and steady aggregate demand (Anand et al., 2014). Ahiadorme (2022) found a positive relationship between decreased income disparity, improved poverty alleviation, and increased inclusivity when low inflation and steady economic growth exist in a country. The research findings corroborate Ghouse et al. (2022), who found that inflation significantly and negatively impacts inclusive growth in low and middle-income countries.

Population growth was negative and significant at a 1% significance level. The sign and magnitude indicate that a percentage increase in population growth will lead to a 0.0972 decrease in inclusive growth. The global population is expected to grow to 9.7 billion by 2050 and 10.9 billion by 2100 (Gu et al.,2021). Increased demand for limited resources such as water, food, cloth, land, etc, can be under pressure due to a population increase. This may result in fewer individuals having access to necessities. The findings are consistent with Pham et al. (2024), who also showed that population growth has a negative, significant impact on inclusive growth. Tella and Alimi (2016) also found that population growth deteriorates inclusive growth.

The findings further reveal that the age dependency ratio positively and significantly affects inclusive growth at a 5% significance level. The sign and magnitude show that when the l age dependency ratio increases by a percentage point, inclusive growth will increase by 0.3452. This finding is surprising, as an increase in the age dependency ratio often results in economic difficulties, implying more dependent people than those who qualify to work or seek employment. Nonetheless, the findings are consistent with findings from Tella and Alimi (2016), who found that age dependency positively and significantly impacts inclusive growth. The rest of the variables – general government final consumption expenditure (% of GDP), GNI per capita (constant 2015 US$), and institutional quality were, however, found to be insignificant in both the system-GMM and difference-GMM estimation techniques.

Prior to the interpretation of the primary regression coefficients, a series of diagnostic tests were conducted to ensure the robustness of the estimated models and the validity of statistical inference. A key assumption in panel data analysis is the cross-sectional independence of error terms. The presence of unobserved common factors can lead to cross-sectional dependence (CSD), which, if ignored, renders standard estimators inefficient and their associated test statistics inconsistent.

To formally assess this, Pesaran's (2004) test of cross-sectional independence was employed post-estimation. The null hypothesis (H_0) for this test is that the residuals across the cross-sectional units are contemporaneously uncorrelated.

The test yielded the following result:

Pesaran's CD statistic = -0.137 (p-value = 0.891)

The test statistic is not statistically significant at any conventional level (e.g., 1%, 5%, or 10%). Consequently, the null hypothesis of cross-sectional independence cannot be rejected. This finding indicates that the error terms of the entities in the panel are not subject to significant common shocks or spatial correlations that would bias the standard errors.

Therefore, based on the Pesaran CD test, the model does not suffer from substantial cross-sectional dependence. This result provides a firm foundation for relying on the standard covariance matrix estimators and the subsequent inference drawn from the panel regression estimates, affirming the internal validity of the model's specification for this dataset.

4.8.2 System GMM Results – Model 2

This section presents the regression results of inclusive growth's effect on poverty in EMDEs.

Table 4. 16: System-GMM and Difference-GMM Outcomes

	Model	
Variables	**System-GMM**	**Difference-GMM**
lnPOV(-1)	1.0364***(0.0148)	1.0256***(0.0636)
lnIG	-0.0415 **(0.0206)	-0.0378 (0.1294)
INF	0.0001**(0.0000)	-2.58e-06 (0.0000)
lnBM	0.0240 (0.0233)	0.0576* (0.0333)
IQI	0.0209 (0.0190)	-0.0625*(0.0357)
GDPGrowth	-0.0050 **(0.0018)	0.0059 **(0.0020)
lnDFII	-0.0240 * (0.0138)	0.0198 (0.0132)
lnGOVEXP	-0.0548**(0.0257)	-0.0751 (0.0631)
PG	0.0001 (0.00923)	0.1172***(0.0362)
Intercept	-0.7571**(0.3104)	
	Diagnostics	
Autocorrelation-Arrelano-Bond test (AR2)	0.47 [0.639]	0.67 [0.501]
Sargan test of overidentifying restrictions	8.15 [0.700]	4.69 [0.455]
Hansen test of overidentifying restrictions	7.58 [0.751]	4.73 [0.449]
Frees' test of cross-sectional independence (at 5% significance level)	3.489 [0.3429]	3.489 [0.3429]

POV: Poverty; IG: Inclusive Growth; INF: Inflation; BM: Broad Money to GDP (Money Supply); IQI: Institutional Quality Index; GDP Growth: Gross Domestic Product growth; DFII: Digital Financial Inclusion Index; General government final consumption expenditure (% of GDP); PG: Population Growth.

Note: Poverty is the dependent variable
The number of observations is 189
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*
() denote the robust standard errors
[] denote the probability values

Source: Calculated by the author in Stata 18

Table 4.16 illustrates the results of the system-GMM and difference-GMM estimation techniques. Although System-GMM was the main estimation technique, the difference-GMM was employed for comparison and robustness checks. GMM estimation techniques and eight

explanatory variables were used. These are: inclusive growth, inflation, broad money to GDP (Money Supply); institutional quality index, GDP Growth, digital financial inclusion index, general government final consumption expenditure (% of GDP), and population Growth. Table 4.15 further shows five (5) of the eight (8) explanatory variables are significant. The coefficient values show that the explanatory variables vary in the degree of impact.

The system GMM estimation technique was the basis for interpreting Model 2 results for reasons already stated in the Model 1 results discussion section. The main explanatory variable (inclusive growth) is significant only under the system-GMM estimation technique. The findings reveal that inclusive growth has a negative, significant effect on poverty in EMDEs at a 5% significance level. The sign and magnitude indicate that when inclusive growth increases by a percentage point, poverty will decrease by 0.0415%.

Concerns over rising inequality despite economic growth have culminated in an increasing awareness of the significance of inclusive growth and development in international development (Kuss et al., 2022). This confirms that inclusive growth is critical in poverty alleviation, particularly in EMDEs where poverty is more prevalent. Effective and fair distribution of resources for the greater good of society is essential to advance an inclusive economy (Singh, 2017) and poverty reduction. The findings are consistent with Amponsah et al. (2023), who found that inclusive growth decreases the adverse effects of income disparity on poverty and can help in reducing it.

As a control variable, inflation significantly and positively affects poverty in EMDEs. For a percentage point increase in inflation, poverty will increase by a small magnitude of 0.0001. Inflation is one of the major concerns for policymakers in both advanced economies and EMDEs (Hassan et al., 2016). Basic goods and products become more expensive because of inflation, making it particularly difficult for households in EMDEs, especially for some of the selected countries in our data such as Zimbabwe, Pakistan, Senegal, Samoa, Rwanda, Mauritius, Guinea, Ghana, Burkina Faso and Botswana, which in 2022 each had annual inflation rates above 10%. Our results are consistent with findings from Omoniyi (2018), and Sehrawat et al. (2018). Baloch et al. (2020) also found that the purchasing power of individuals is reduced by inflation, thus forcing them to settle for products of lower quality that exacerbate poverty.

Gross domestic product (GDP) growth was found to be significant at a 5% significance level. The sign and magnitude suggest that a percentage point increase in GDP growth will lead to a marginal decrease of 0.0050 units in poverty. The United Nations aims to end extreme poverty – as measured by the proportion of individuals who live on less than USD1.25 a day. However, recent studies suggest that economic growth by itself is unlikely to reach this goal (Anderson et al., 2018). The findings corroborate those of Anyanwu et al. (2013), who found that an increase in real per capita GDP has a considerable negative impact on poverty levels, thus contributing positively to poverty alleviation. Although economic growth is essential, comprehensive policies that promote economic inclusion should be considered and implemented effectively and efficiently to ultimately experience poverty reduction through economic growth.

Digital financial inclusion negatively and significantly affects poverty in EMDEs at a 10% significance level. For a percentage point increase in digital financial inclusion, poverty will decrease by a magnitude of 0.0240. The World Bank deems individuals to be financially included if they have a bank account or a digital wallet (Ogbeide & Igbinigie, 2019). Most impoverished individuals are unable to access financial products and services such as loans through traditional financial institutions as physical branches are at times too far and it is expensive for individuals to reach them. Nonetheless, digital financial services make it possible for impoverished individuals to have access to essential financial products and services without visiting a branch. This provides individuals with the opportunity to manage their money more efficiently and effectively. The findings correspond with Lee et al. (2023) who demonstrated that the growth of digital financial inclusion considerably lowers and stabilises the overall level of poverty.

Government expenditure negatively and significantly affects poverty in the selected EMDEs of our study at a 5% significance level. The sign and magnitude suggest that a percentage point increase in government expenditure will lead to a decrease of 0.0548 units in poverty. Global economic growth and the fight against poverty are significantly facilitated by government expenditure (Chude et al., 2019). However, for government expenditure to be effective, it needs to be targeted at the right initiatives aimed at improving and empowering society. Nevertheless, in some cases, resources might be squandered and thus fail to reach the intended target market due to corruption. These findings align with those reported by Mehmood and Sadiq (2010).

However, the rest of the variables; broad money to GDP, institutional quality, and population growth were found to be insignificant under the system-GMM estimation technique.

4.9 Concluding Remarks

This study sought to investigate how digital financial inclusion affects poverty through inclusive growth EMDEs. This was achieved through the application of panel estimation techniques.

This chapter has explored the theoretical foundations of the effect of digital financial inclusion on inclusive growth and poverty in EMDEs through the perspective of the theory of financial intermediation. Financial intermediation is also based on the transaction costs approach established by Benston and Smith (1976) and Fama (1980). High transaction costs deter people from taking part in the formal financial sector, which eventually leads to greater financial exclusion, high poverty levels, and low inclusive growth. Conversely, lower transaction costs typically lead to greater inclusive growth, poverty reduction, and increased digital financial inclusion.

The literature review demonstrates that in most regions with EMDEs, digital financial inclusion plays a role in increasing inclusive growth. Moreover, existing literature also shows that poverty can be reduced through inclusive growth. Additionally, financial inclusion is a solid foundation for the financial infrastructure of any country (Liagat et al., 2022). Most studies in our empirical literature demonstrated that digital finance does reduce poverty and is closely related to the advancement and expansion of inclusive economic growth. Furthermore, studies have shown that financial inclusion is a powerful tool for reducing poverty, particularly in EMDEs.

This study constructed a new multidimensional digital financial inclusion index for 21 EMDEs using weights derived from the PCA in aggregating indicators for two dimensions, that is, access and usage, following Camara and Tuesta (2014) and Khera et al., (2022). The index is a useful tool for evaluating the degree of digital financial inclusion in various EMDEs and tracking their development over time. In our analysis, using data spanning from 2013 to 2022, we found that none of the countries we selected demonstrated a high level of digital financial

inclusion in the time frame we examined, applying the ranking systems developed by Camara and Tuesta (2014). Zimbabwe and Rwanda demonstrated a moderate level of digital financial inclusion, whereas Ghana showed a medium level of digital financial inclusion in 2020 and 2021. Moreover, the EMDEs selected for the study all fall under the low-level category since their average level of digital financial inclusion from 2013 to 2021 is less than 30%. Considering this, policymakers and governments should take it upon themselves to ensure that correct policies and programs are made available to meet the needs of the underserved and previously disadvantaged populations in EMDEs.

The main objective of this study was to employ the system-GMM estimation technique to examine how digital financial inclusion affects poverty through inclusive growth EMDEs. This was achieved by first estimating the effect of digital financial inclusion on inclusive growth (scenario 1) and then estimating the effect of inclusive growth on poverty in EMDEs (scenario 2). Under the first scenario, the study found that digital financial inclusion (main explanatory variable) was significant under the system-GMM estimation technique. The results show that on the main independent variable (that is, inclusive growth), digital financial inclusion has a positive and significant effect on inclusive growth in EMDEs at a 10% significance level. The sign and magnitude indicate that when digital financial inclusion increases by a percentage point, inclusive growth will increase by a magnitude of 0.7428 units.

Some control variables also showed that they were significant to the dependent variable, digital financial inclusion. These control variables included inflation, population growth, and the age dependency ratio. Nonetheless, general government final consumption expenditure (% of GDP), GNI per capita (constant 2015 US$), and institutional quality were found to be insignificant to digital financial inclusion. Policymakers and governments should consider prioritising capital or investments in industries with the greatest prospects of increasing inclusive growth through digital financial inclusion. This can be made possible through increasing access to digital financial services and products, particularly in areas where financial exclusion is severe.

Under the second scenario, the study found that inclusive growth (the main explanatory variable) is significant under the system-GMM estimation technique. The findings demonstrate that inclusive growth has a negative and significant effect on poverty in EMDEs at a 5% significance level. The sign and magnitude indicate that when inclusive growth increases by a percentage point, poverty will decrease by a magnitude of 0.0415 units. Some control variables

also demonstrated that they were significant to the dependent variable, poverty. These control variables included inflation, Gross domestic product (GDP) growth, digital financial inclusion, and general government final consumption expenditure (% of GDP). The rest of the variables, that is, broad money to GDP, institutional quality, and population growth were however found to be insignificant under the system-GMM estimation technique. By developing channels and policies that will aid in reducing income inequality, and increasing job opportunities for all, policymakers and governments can alleviate poverty through inclusive growth in EMDEs. When job opportunities are increased, participation in the workforce is also likely to increase, particularly amongst poor individuals who are often without work.

CHAPTER 5

SUMMARY, CONCLUSIONS, AND POLICY RECOMMENDATIONS

5.1 Introduction

This chapter provides a summary of the key findings of the chapters of the thesis. It entails four subsections: a summary of key findings from the research, contribution and research implications, limitations and directions for future research, and the closing statement.

5.2 Summary of Key Findings from the Research

The study investigated the relationship between FinTech and financial inclusion in EMDEs. The investigation was conducted to close the gaps identified in the existing literature regarding the relationship between FinTech and financial inclusion. Institutions are essential for the functioning of financial markets. Therefore, the effect of institutional quality on digital financial inclusion in EMDEs was also examined. Poverty and inclusive growth are closely related and essential for equitable growth. It is for this reason that this study examined the effect of digital financial inclusion on poverty through the intervention of inclusive growth. The summary of key findings is presented in line with the research objectives (ROs), on which each study was based.

5.2.1 The Relationship Between FinTech and Financial Inclusion (RO1)

The study sought to estimate the impact of FinTech on financial inclusion in 28 EMDEs and employed the system-GMM estimation technique. The study found that FinTech has a significant positive effect on financial inclusion in EMDEs. This implies that people, particularly the underserved population, will become a part of the financial landscape when they adopt FinTech since it will give them access to financial services and products. Moreover, inflation was found to have a significant negative effect on financial inclusion, indicating that there is an inverse relationship between inflation and financial inclusion in EMDEs. Finally, broad money to GDP was also found to be positively significant to financial inclusion in EMDEs. Broad money to GDP has an impact on financial inclusion as it affects the cost of financial services and products.

The study also assessed the factors that impact barriers to financial inclusion in the 28 EMDEs using the OLS technique. The study found that education positively and significantly impacts barriers to financial inclusion. This finding illustrates that educated individuals are likely to make well-informed decisions when they make use of financial services and products, as they are better equipped to comprehend the range of financial products available. Additionally, GNI per capita has a negative and significant impact on barriers to financial inclusion, thus indicating that an increase in GNI per capita will result in a decrease in barriers to financial inclusion. Furthermore, broad money to GDP was found to negatively and significantly impact the barriers to financial inclusion, indicating that an increase in broad money to GDP leads to a decrease in barriers to financial inclusion.

5.2.2 The Effect of Institutional Quality on Digital Financial Inclusion (RO2)

This study sought to examine the effect of institutional quality on digital financial inclusion in EMDEs in both the short and long run. This was done by employing the panel ARDL technique.

The study found that institutional quality has a positive and significant effect on digital financial inclusion in EMDEs. The results of the study reveal that an increase in institutional quality leads to an increase in digital financial inclusion in the long run. Robust institutions can aid in ensuring the safety, reliability, and access to digital financial services. Furthermore, inflation was found to significantly and negatively affect digital financial inclusion in EMDEs in the long run. This suggests that the relationship between digital financial inclusion and inflation is inverse. Further findings reveal that education significantly and positively affects digital financial inclusion in the long run. The finding shows that an increase in the level of education leads to an increase in digital financial inclusion. Education equips individuals with skills to use digital services and improves their understanding of finances.

Moreover, the results reveal that, in the long run, gross national income per capita impacts digital financial inclusion positively and significantly. This illustrates that an increase in gross national income per capita leads to an increase in digital financial inclusion. Furthermore, Domestic credit to the private sector by banks (% of GDP) was found to have a negative and significant impact on digital financial inclusion in EMDEs in the long run. Population growth was found to have a positive and significant impact on digital financial inclusion in the long run. This suggests that an increase in population growth will lead to an increase in digital

financial inclusion. Lastly, General government final consumption expenditure (% of GDP) was also found to be significant to digital financial inclusion.

In the short run, inflation was found to significantly and negatively affect digital financial inclusion. Trade (% of GDP) was also found to significantly and positively affect digital financial inclusion in the short run.

5.2.3 The Effect of Financial Inclusion on Inclusive Growth and Poverty (RO2)

The main objective of this study was to employ the system-GMM estimation technique to examine how digital financial inclusion affects poverty through inclusive growth in EMDEs. This was achieved by first estimating the effect of digital financial inclusion on inclusive growth (scenario 1) and then estimating the effect of inclusive growth on poverty in EMDEs (scenario 2).

Under the first scenario, the study found that digital financial inclusion has a positive and significant effect on inclusive growth in EMDEs. One of the key elements required to achieve inclusive growth is digital financial inclusion. Additionally, inflation significantly and negatively affects inclusive growth, thus signifying that there is an inverse relationship between inflation and inclusive growth. Population growth was found to be negative and significant to inclusive growth. The results reveal that when population growth increases, inclusive growth decreases. Increased population can put pressure on limited resources, leading to economic exclusion for some individuals. Further findings revealed that the age dependency ratio positively and significantly affects inclusive growth.

Under the second scenario, the study found that inclusive growth has a negative and significant effect on poverty. This means that an increase in inclusive growth leads to a decrease in poverty. This is an indication that inclusive growth plays a vital role in poverty alleviation, particularly in EMDEs where poverty is more prevalent. The findings further reveal that inflation significantly and positively affects poverty in EMDEs. Inflation is a top priority for policymakers in both developed and developing countries. GDP growth was found to have a positive and significant impact on poverty. Digital financial inclusion negatively and significantly affects poverty, thus illustrating that an increase in digital financial inclusion leads to a decrease in poverty. Lastly, government expenditure positively and significantly affects

poverty. This finding suggests that an increase in government expenditure leads to an increase in poverty.

5.3 Contribution and Research Implications

This thesis ventures beyond conventional analysis, delivering significant contributions across knowledge, methodology, and conceptual understanding. It introduces innovative indices, adopts a *unique digital perspective*, and pioneers the examination of how digital financial inclusion impacts poverty via inclusive growth, illuminating previously unexplored pathways.

5.3.1 Research Contribution

5.4 Contribution of the Study

a) *A Cross-Country Analysis of EMDEs*

FinTech has emerged as a revolutionary phenomenon relating to financial inclusion, particularly in EMDEs. Through innovative solutions, FinTech can fundamentally change how financial services are offered and accessed in EMDEs. Previous studies show that the nexus between FinTech and financial inclusion has primarily been concentrated on specific countries at a point and time as opposed to a cross-country analysis; this creates an opportunity for further investigation. This study contributes to the body of knowledge by examining the relationship between FinTech and financial inclusion by focusing on EMDEs in Africa, Asia, Emerging Europe, Latin America, and the Caribbean, as these regions have received very little attention from previous studies.

b) *Policy Implications*

By simultaneously analysing the EMDEs, information sharing is made easier, thus enabling countries to learn from successful FinTech solutions from other countries to help solve their financial exclusion problems. This study shows that FinTech has a positive impact on financial inclusion in EMDEs. Therefore, policymakers and governments should channel capital into innovative financial solutions to help reduce financial exclusion as this has the potential to reduce poverty and increase economic growth.

c) *Highlighting Barriers to FinTech-Driven Financial Inclusion*

Furthermore, this study's other unique contribution to research is that it incorporates barriers to financial inclusion when examining the relationship between FinTech and financial inclusion. By highlighting the barriers to financial inclusion alongside the benefits of FinTech, this study equips policymakers and researchers with a nuanced understanding of the distinct challenges faced by various developing countries. This knowledge can inform the design of targeted interventions and policies that promote the adoption of FinTech and address the specific barriers that hinder financial access.

d) *Digital Perspective on Institutional Quality and Financial Inclusion*

The widespread adoption of digital financial services allows developing countries to reduce financial exclusion and improve economic growth. Nonetheless, the quality of the institutions in which these digital financial services operate determines their impact on the financial market. This study examined the effect of institutional quality on digital financial inclusion in EMDEs. This study's unique contribution to the body of knowledge is that, unlike the existing literature that assessed financial inclusion from a traditional perspective (Aribatise, 2022; Anthony-Orji et al., 2019; Nkoa & Song, 2020; Van et al., 2022; Qamruzzaman & Wei, 2019), this study empirically assessed financial inclusion from a digital perspective on institutional quality.

e) *Methodological Innovation: PCA-Based Digital Financial Inclusion Index*

Digital financial inclusion indicators and dimensions were employed to construct a new digital financial inclusion index. Unlike Sarma (2008), who applied the non-parametric approach whereby the weights of the dimensions are assigned subjectively by the researcher, the current study employed the principal component analysis (PCA) approach when constructing the institutional quality index and digital financial inclusion index. The PCA technique scientifically calculates the weights for each dimension instead of manually assigning them, and it also eliminates the correlated variables that do not contribute to decision-making. Thus, the indices constructed are robust. Most studies have focused on assessing specific individual countries at a time as opposed to doing a cross-country assessment, presenting a gap in the literature. This study contributes to the limited literature on EMDEs regarding institutional quality and digital financial inclusion.

f) *Digital Financial Inclusion, Poverty, and Inclusive Growth in EMDEs*

This study further investigated the effect of digital financial inclusion on poverty through the intervention of inclusive growth in EMDEs, as literature in this area is limited, thus presenting a gap to explore. Given the close relationship between poverty and inclusive growth, it is imperative to investigate how digital financial inclusion impacts them. Examining how digital financial inclusion impacts poverty through inclusive growth is crucial since these two factors are closely connected. Unlike the existing literature, the present study included a cross-country analysis instead of focusing on one specific country or region. The study focused on Central Africa, Southern Africa, West Africa, Oceania, West Asia and South Asia as there is a dearth of similar research in these regions. Furthermore, when constructing the financial inclusion index, the present study employed digital dimensions and indicators rather than traditional ones. This is a unique contribution to existing literature, as most studies used traditional dimensions and indicators to construct a financial inclusion index. Moreover, this study employed the System-Generalized Method of Moments (GMM) as the estimation technique because it offers reliable and effective estimates, solves the endogeneity issue, and better fits panel studies. This adds to the uniqueness of the study as well.

g) *Contribution to Knowledge*

In the *first objective (RO1)*, the study constructed a new multidimensional financial inclusion index for 28 EMDEs using the PCA technique. The study also constructed a new FinTech index. Moreover, a new barriers index was developed by employing the PCA technique. The study revealed that when individuals accept and adopt FinTech, they will have access to financial products and services and will, therefore, be included in the financial landscape. This demonstrates that FinTech drives financial inclusion. Furthermore, through a cross-country analysis, the study investigated factors that impact barriers to financial inclusion in EMDEs. This is an enhancement of existing literature that only focused on dimensions (demand and supply) that impact financial inclusion.

h) *Methodological Contribution*

In the *second objective (RO2)*, the study constructed a new multidimensional digital financial inclusion index for 25 EMDEs using the PCA technique. The index offers a consistent way to track progress across different countries by allowing a cross-country comparison of the level

of digital financial inclusion. Unlike existing literature that investigated the relationship between institutional quality and financial inclusion from a traditional standpoint, this study examined the relationship between these two factors from a digital perspective. Findings from the study revealed that institutional quality has a positive effect on digital financial inclusion in the long run but not in the short run.

i) *Conceptual And Analytical Contribution*

In the *third objective (RO3)*, the study examined the effect of digital financial inclusion on poverty through the intervention of inclusive growth, which is not available in the existing literature. Hitherto, literature has only examined the effect of digital financial inclusion on poverty or the effect of digital financial inclusion on inclusive growth separately.

5.4.1 Practical and Policy Implications

This thesis, through robust panel and OLS estimations across 28 EMDEs, has illuminated the significant role of FinTech in driving financial inclusion alongside the key factors that impede it. Based on the findings, the study makes the following recommendations to policymakers. The recommendations are linked to the findings per research objective (RO).

1. Investment in Digital Payment Infrastructure (RO1)

    - Prioritise strategic investments in digital payment infrastructure.
    - Develop affordable and accessible financial services.
    - Implement targeted initiatives to address the needs of financially excluded populations.
    - Expand mobile connectivity and internet access, especially in underserved regions.

2. Strengthening Institutional Frameworks (RO2)

    - Foster cost-effective and efficient internet infrastructure.
    - Encourage collaboration between governments and financial institutions.
    - Cultivate an enabling environment for digital financial inclusion.
    - Strengthen institutional frameworks to benefit marginalised individuals and bolster overall financial inclusion.

3. Promoting Inclusive Growth for Poverty Reduction (RO3)

    - Implement channels and policies aimed at reducing income inequality.
    - Expand job opportunities for all.
    - Stimulate workforce participation, particularly among impoverished individuals.
    - Harness digital financial inclusion as a tool to promote inclusive growth and reduce poverty.

Implementing these recommendations is crucial for EMDEs to unlock the transformative potential of digital financial inclusion, fostering equitable economic growth and substantially reducing poverty.

5.4.2 Limitation and Direction for Future Studies

The greatest challenge experienced by the study has to do with data, especially for constructing the digital financial inclusion index. This prevented the inclusion of more countries in the study. The empirical findings of this thesis suggest the following recommendations for future research:

1. Concerning the relationship between FinTech and financial inclusion, future research could employ different estimation techniques from this study to determine the short- and long-term impact of FinTech on financial inclusion in EMDEs.

2. Moreover, it would be beneficial to investigate the effect of institutional quality on digital financial inclusion in both advanced countries and EMDEs to be able to do a cross-country comparison between the developed and developing countries.

3. Lastly, the effect of financial inclusion on inclusive growth and poverty in EMDEs could be examined by employing different measures for inclusive growth and poverty.

These research recommendations are vital for expanding the understanding of digital financial inclusion's impact across diverse contexts and methodologies, ultimately strengthening the evidence base for effective policy interventions.

5.5 Conclusion

It is widely accepted that financial inclusion is a powerful instrument for reducing poverty, promoting inclusive growth, and strengthening financial stability. FinTech is an essential instrument that can promote financial inclusion, given that it can reduce bank operating costs by enabling branchless technology-based banking. This study contributes to empirical literature by examining the relationship between FinTech and financial inclusion in Africa, Asia, the Middle East, Eastern Europe, Latin America, and the Caribbean, as these regions have a higher prevalence of financial exclusion and thus require more attention. Institutions that are dependable and efficient provide a favourable environment for digital financial services by offering financial stability, innovation, transparency, and safe transactions.

This fosters interest in the formal financial sector amongst individuals and potential investors, especially those who were previously marginalised. Moreover, digital financial services can lower the rate of poverty by providing impoverished individuals access to fundamental financial services. Digital financial inclusion, particularly in EMDEs, has the potential to break the cycle of poverty through the adoption and use of technology. This can be achieved by emancipating historically disadvantaged individuals and promoting inclusive growth. This study calls for the adoption, access, and use of technology to aid in increasing financial inclusion, reducing poverty rates, and increasing inclusive growth in EMDEs.

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APPENDICES

Appendix A: Unit Root Test Results for Financial Inclusion Dataset

Variable	Levin-Lin-Chui Unit		Hadri	
	Level		Level	
	Constant	Constant +Trend	Constant	Constant +Trend
TFI	-7.7282***	-11.0500***	24.4430***	7.3820***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FINT	-4.2214***	-10.4418***	29.4497***	18.5515***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
TO	-6.4713***	-11.0104***	16.9420***	4.1004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GOVEXP	-3.9776***	-7.7498***	11.7203***	4.5270 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GNI	-2.6829**	-5.3953***	20.7501***	18.1348***
	(0.0036)	(0.0000)	(0.0000)	(0.0000)
BM	-0.4702	-6.5624***	19.3081***	5.6104***
	(0.3191)	(0.0000)	(0.0000)	(0.0000)
INF	-4.8009***	-11.6478***	9.6775***	1.9058**
	(0.0000)	(0.0000)	(0.0000)	(0.0283)

FinTech: Financial Technology; TO: Trade Openness (%GDP); GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); MS: Broad Money to GDP (Money Supply); INF: Inflation
Note: () denote the p-values
****, **, denote the significance at the 1% and 5% levels respectively*

Source. Calculated by the author using Stata 18

Appendix B: Panel Methods Results

	Model			
Variables	**Pooled OLS**	**Fixed Effects**	**Random Effects**	**System-GMM**
lnTFI (-1)				0.7940***(0.0542)
lnFinTech	0.1292***(0.0727)	0.5596***(0.0706)	0.5237***(0.0658)	0.1773**(0.0874)
lnTO	-0.0753 (0.0670)	-0.3632***(0.096)	-0.2985***(0.086)	-0.0679 (0.1271)
lnGOVEXP	-0.0556 (0.0754)	-0.1776 (0.1261)	-0.1329 (0.1107)	0.0472 (0.0711)
lnGNI	0.4307***(0.045)	0.3135***(0.0805)	0.3277***(0.0619)	-0.0917 (0.1115)
lnBM	0.8342***(0.073)	0.6642***(0.1152)	0.6936***(0.1019)	0.2761**(0.1214)
INF	0.0009 (0.0008)	0.0001 (0.0004)	0.0002 (0.0004)	-0.0003**(0.0001)
Intercept	-7.7752***(0.4628)	-4.278*** (0.9949)	-4.9261***(0.7636)	-0.2931 (1.0625)
		Diagnostics		
R-squared	0.7394			
Autocorrelation- Arrelano-Bond test (AR2)				-1.43 [0.153]
Sargan test of overidentifying restrictions				3.29 [0.349]
Hansen test of overidentifying restrictions				1.82 [0.612]
Friedman test of cross-sectional independence		32.442 [0.2161]	32.110 [0.2280]	
F-Test		24.52 [0.000]		
sigma_u		0.5144	0.5002	

sigma_e	0.2132	0.2132
rho	0.8533	0.8462

FinTech: Financial Technology; TO: Trade Openness (% GDP); GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); MS: Broad Money to GDP (Money Supply); INF: Inflation.
Note: Financial inclusion is the dependent variable

Number of observations is 208
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*
() denote the robust standard errors
[] denote the probability values

Source: Calculated by the author in Stata 18

Appendix C: Unit Root Test Results for Barriers Dataset

Variable	Im, Pesaran, and Shin	
	Level	
	Constant	Constant +Trend
BARR	-3.7648***	-3.6888**
	(0.0086)	(0.0407)
EDU	-7.8314***	-7.6703***
	(0.0000)	(0.0000)
GNI	-3.335**	-3.4419*
	(0.0231)	(0.0668)
BM	-4.2536***	-4.7293***
	(0.0026)	(0.0041)
DPR	-3.0764**	-4.277**
	(0.0405)	(0.0115)
DCPS	-5.019***	-6.7152***
	(0.0004)	(0.000)

Note: () denote the p-values
****, **, denote the significance at the 1% and 5% levels, respectively*

Source: Calculated by the author in Stata 18

Appendix D: OLS Estimation Results

Dependent Variable: BAR (2021Y)	
Variable	**Pooled OLS**
EDU	0.0098*
	(0.0040)
GNI	-0.000019*
	(0.0000)
BM	-0.0081**
	(0.0034)
DPR	0.0007
	(0.0068)
DCPS	0.0020
	(0.0040)
Intercept	0.2240
	(0.9603)
Diagnostics	
R-squared	0.5233
F-statistic	5.75
Prob(F-statistic)	0.0015
Shapiro–Wilk W test for normal data	-0.681[0.7521]
Heteroskedasticity	1.36 [0.2431]

Note: Barriers are the dependent variable
The number of observations is 28
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*
[] denotes the probability values
() denotes the robust standard errors

Source: Calculated by the author in Stata 18

Appendix E: Unit Root Test Results for Digital Financial Inclusion Dataset

Variable	Levin-Lin-Chui		Im, Pesaran, and Shin	
	Level		Level	
	Constant	Constant +Trend	Constant	Constant +Trend
DFII	-2.94641**	-5.57254***	2.01744	1.98474**
	(0.0016)	(0.0000)	(0.9782)	(0.0236)
IQI	-3.64309***	-4.85729***	-2.26271**	-5.74668***
	(0.0001)	(0.0000)	(0.0118)	(0.0000)
INF	-5.08320***	-4.71611***	-6.37352***	-6.01433***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
BM	-2.97730**	-4.33402***	-1.33435*	-3.63773***
	(0.0015)	(0.0000)	(0.0910)	(0.0001)
EDU	-5.01628***	-3.12664***	-2.69400**	-3.00759**
	(0.0000)	(0.0009)	(0.0035)	(0.0013)
GNI	-4.91147***	-4.60132***	-2.10161	-2.64043**
	(0.0000)	(0.0000)	(0.0178)	(0.0041)
DCPS	-4.37132***	-4.96239***	-2.27232*	-4.14199***
	(0.0000)	(0.0000)	(0.0115)	(0.0000)
	-5.09134***	-5.20262***	-2.03402**	-1.77402**
PG	(0.0000)	(0.0000)	(0.0210)	(0.0380)
	-4.09073***	-3.51064***	-3.04946**	-2.40246**
TO	(0.0000)	(0.0002)	(0.0011)	(0.0081)
	-3.37645***	-3.28046***	-2.29479*	-2.60715**
GOVEXP	(0.0004)	(0.0005)	(0.0109)	(0.0046)

Note: () denote the p-values

****, **, denote the significance at the 1% and 5% levels respectively*

DFII: Digital Financial Inclusion Index; IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); DCPS: Domestic credit to private sector by banks (% of GDP); PG: Population growth (annual %); TO: Trade Openness (% of GDP); GOVEXP: General government final consumption expenditure (% of GDP).

Source: Calculated by the author in Stata 18

Appendix F: Long-Run Effects – Institutions and Digital Financial Inclusion

Variable	Coefficient	Standard Error	t-Statistic
IQI	0.5887***	0.0126	46.8724
INF	-0.0031**	0.0016	-2.0392
lnBM	-0.0395	0.0844	-0.4683
lnEDU	0.2898**	0.1096	2.6445
lnGNI	0.3515***	0.0506	6.9541
lnDCPS	-0.1364**	0.0525	-2.5988
PG	0.5747***	0.0475	12.0988
lnTO	0.006273	0.0592	0.1059
lnGOVEXP	-0.2716***	0.0647	-4.1951
Constant	5.6168***	1.0696	5.2513

Note: Financial inclusion is the dependent variable
The number of observations is 875
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*
IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); DCPS: Domestic credit to private sector by banks (% of GDP); PG: Population growth (annual %); TO: Trade Openness (% of GDP); GOVEXP: General government final consumption expenditure (% of GDP).

Source: Calculated by the author in Eviews13

Appendix G: Short-Run Effects – Institutions and Digital Financial Inclusion

Variable	Coefficient	Standard Error	t-statistic
ΔIQI	0.2005	0.2870	0.6984
ΔINF	-0.0399*	0.0237	-1.6868
ΔlnEDU	-0.0992	4.6404	-0.0213
ΔlnGNI	-1.0968	1.9395	-0.5654
ΔlnDCPS	-0.2451	0.8622	-0.2843
ΔPG	-0.0326	1.7574	-0.0185
ΔlnTO	0.7767*	0.4427	1.7544
ΔlnGOVEXP	-0.2884	1.1213	-0.2572
Cointegration	-0.0409***	0.01073	-3.8092

Note: Financial inclusion is the dependent variable
The number of observations is 875
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*
IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); DCPS: Domestic credit to private sector by banks (% of GDP); PG: Population growth (annual %); TO: Trade Openness (% of GDP); GOVEXP: General government final consumption expenditure (% of GDP).

Source: Calculated by the author in Eviews13

Appendix H: Unit Root Test Results for Digital Financial Inclusion Dataset

Variable	Levin-Lin-Chui		Hadri LM	
	Level		Level	
	Constant	Constant +Trend	Constant	Constant +Trend
DFII	-5.3821*** (0.0000)	-1.6054 ** (0.0542)	15.1448*** (0.0000)	1.4404 * (0.0749)
IG	-2.9160*** (0.0000)	-3.9809*** (0.0000)	15.1065*** (0.0000)	6.0057 **** (0.0000)
POV	-1.7285 ** (0.0420)	-6.2368*** (0.0000)	22.1750*** (0.0000)	1.3221* (0.0931)
DPR	9.2393 (1.0000)	-3.1925*** (0.0007)	22.4054*** (0.0000)	13.7787*** (0.0000)
IQI	-7.5343*** (0.0000)	-8.7303*** (0.0000)	8.6789*** (0.0000)	3.7162*** (0.0001)
INF	1.8300 (0.9664)	-4.0878*** (0.0000)	5.8073*** (0.0000)	-0.1282 (0.5510)
BM	-1.4876* (0.0684)	-4.9217*** (0.0000)	16.2548*** (0.0000)	2.0409** (0.0206)
GDP Growth	-5.8753*** (0.0000)	-8.6426 *** (0.0000)	-0.0757 (0.5302)	-0.0783 (0.5312)
EDU	-4.2329*** (0.0000)	-6.8878*** (0.0000)	15.9326*** (0.0000)	5.6781*** (0.0000)
GNI	7.2128 (1.0000)	9.8274 (1.0000)	3.6377*** (0.0001)	3.8019*** (0.0001)
PG	1.7091 (0.9563)	-3.1519*** (0.0008)	15.8107*** (0.0000)	10.9203*** (0.0000)
GOVEXP	-3.8951*** (0.0000)	-2.0130** (0.0221)	8.4703*** (0.0000)	3.1472*** (0.0008)

DFII: Digital Financial Inclusion Index; IG: Inclusive Growth; POV: Poverty; DPR: Age Dependency Ratio; IQI: Institutional Quality Index; INF: Inflation; BM: Broad money to GDP; EDU: Education; GNI: GNI per capita (constant 2015 US$); PG: Population growth (annual %); GOVEXP: General government final consumption expenditure (% of GDP).

****, *** denote the significance at the 1%, 5% and 10% levels respectively*

Note: () denote the p-values Source:

Calculated by the author in Stata 18

Appendix I: System-GMM and Difference-GMM Outcomes

Model		
Variables	**System-GMM**	**Difference-GMM**
lnIG (-1)	0.7428***(0.1398)	0.7754*** (0.0845)
lnDFII	0.0227*(0.0128)	-0.00125392
INF	-0.0003***(0.0000)	-0.0001(0.0001)
PG	-0.0972***(0.0266)	-0.0698**(0.0001)
lnGOVEXP	-00630 (0.0491)	-0.1520(0.1026)
lnGNI	0.1621(0.1622)	0.2084 (0.2969)
lnDPR	0.3452 **(0.1543)	-1.2349 **(0.5498)
IQI	0.0286(0.0272)	-0.0285 (0.0322)
Intercept	-0.0000 (0.9428)	
	Diagnostics	
R-squared		
Autocorrelation- Arrelano-Bond test (AR2)	0.96 [0.336]	0.67 [0.502
Sargan's test of overidentifying restrictions	6.78 [0.452]	0.48 [0.786]
Hansen's test of overidentifying restrictions	4.83 [0.681]	0.93 [0.628]
Friedman's test of cross-sectional independence	17.810 [0.5999]	17.810 [0.5999]

IG: Inclusive Growth; DFII: Digital Financial Inclusion Index; INF: Inflation; PG: Population growth (annual %); GOVEXP: General government final consumption expenditure (% of GDP); GNI: GNI per capita (constant 2015 US$); DPR: Age dependency ratio; IQI: Institutional Quality Index.

Note: Inclusive Growth is the dependent variable
The number of observations is 189
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*
() denote the robust standard errors
[] denote the probability values

Source: Calculated by the author in Stata 18

Appendix J: System-GMM and Difference-GMM Outcomes

Model		
Variables	**System-GMM**	**Difference-GMM**
lnPOV(-1)	1.0364***(0.0148)	1.0256***(0.0636)
lnIG	-0.0415 **(0.0206)	-0.0378 (0.1294)
INF	0.0001**(0.0000)	-2.58e-06 (0.0000)
lnBM	0.0240 (0.0233)	0.0576* (0.0333)
IQI	0.0209 (0.0190)	-0.0625*(0.0357)
GDPGrowth	-0.0050 **(0.0018)	0.0059 **(0.0020)
lnDFII	-0.0240 * (0.0138)	0.0198 (0.0132)
lnGOVEXP	-0.0548**(0.0257)	-0.0751 (0.0631)
PG	0.0001 (0.00923)	0.1172***(0.0362)
Intercept	-0.7571**(0.3104)	
	Diagnostics	
Autocorrelation-Arrelano-Bond test (AR2)	0.47 [0.639]	0.67 [0.501]
Sargan test of overidentifying restrictions	8.15 [0.700]	4.69 [0.455]
Hansen test of overidentifying restrictions	7.58 [0.751]	4.73 [0.449]
Frees' test of cross-sectional independence (at 5% significance level)	3.489 [0.3429]	3.489 [0.3429]

POV: Poverty; IG: Inclusive Growth; INF: Inflation; BM: Broad Money to GDP (Money Supply); IQI: Institutional Quality Index; GDP Growth: Gross Domestic Product growth; DFII: Digital Financial Inclusion Index; General government final consumption expenditure (% of GDP); PG: Population Growth.

Note: Poverty is the dependent variable
The number of observations is 189
****, **, * denote the significance at the 1%, 5%, and 10% levels respectively*
() denote the robust standard errors
[] denote the probability values

Source: Calculated by the author in Stata 18