FinTech as a Catalyst for Economic Growth and SDG Attainment: The Role of FDI Across Income-Level Economies

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BY

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DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of my own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal

(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) The word count of this research report is 45865.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey–Fuller
AI	Artificial Intelligence
CFPS	China Family Panel Studies
CLT	Central Limit Theorem
DEA	Data Envelopment Analysis
EBM	Epsilon-Based Measure
EGT	Endogenous Growth Theory
FAS	International Monetary Fund's Financial Access Survey
FDI	Foreign Direct Investment
FEM	Fixed Effects Model
FSB	Financial Stability Board
GDP	Gross Domestic Product
GETS	General-to-Specific
GFCF	Gross fixed capital formation
GLS	Generalized Least Squares
GMM	Generalized Method of Moments
GNI	Gross National Income
HDI	Human Development Index
HFCE	Households and NPISH Final Consumption Expenditure
IFZ	Financial Service Zug
IMF	International Monetary Fund
IPA	Investment Promotion Agencies
ITU	International Telecommunication Union
NPISH	Non-Profit Institutions Serving Households

OECD	Organization for Economic Cooperation and Development
OFDI	Outward FDI
PCA	Principal Component Analysis
PSTR	Panel Smooth Transition Regression
PTR	Panel Threshold Regression
REM	Random Effects Model
RENC	Renewable Energy Consumption
SBM	Slack-Based Measure
SDG	Sustainable Development Goals
SDGI	Sustainable Development Goals Index
SDSN	Sustainable Development Solution Networks
SEM	Structural Equation Modeling
SIC	Standard Industrial Classification
SSA	Sub-Saharan Africa
SWIID	Standardised World Income Inequality Database
VIF	Variance Inflation Factors
WDI	World Bank: World Development Indicators
WEF	World Economic Forum

PREFACE

Firstly, as a FinTech student, I have always been fascinated by the rapid growth of digital technology and its potential to support sustainable development and economic growth. Besides, I am particularly interested in how technology can make financial services more accessible and create positive social and economic impacts across different countries, as the trend is growing in this era. This research gave me the opportunity to explore these issues in depth, examine development trends in various nations, and better understand how income levels influence the impact of FinTech. Beyond the research itself, this experience has also strengthened my research skills and deepened my knowledge on the relationship of FinTech, FDI, macroeconomic performance, and the achievements of SDGs.

ABSTRACT

Although FDI and FinTech are increasingly acknowledged as important development drivers, their effects are complicated, and empirical results are frequently contradictory and inconsistent among nations with different income levels. Despite extensive research, existing research often analyzes FinTech and FDI in isolation, overlooking their combined effects and the mediating role of FDI in translating financial innovation into broader development outcomes. Additionally, many studies use limited indicators for FinTech and focus on individual SDGs rather than their aggregate impact, creating a gap in holistic understanding. Consequently, this research aims to compare FinTech development across income levels and to examine both the direct and indirect impacts of FinTech and FDI on macroeconomic performance and SDG attainment. Specifically, this research utilizes a balanced panel dataset for 54 countries, categorized into four income groups, covering the period from 2017 to 2023. Specifically, this research will employ descriptive statistics, the Kruskal-Wallis Test, and panel regression models to test the hypotheses. Overall, the study finds that FinTech development remains in its infant stage, particularly in lower-income economies. Consequently, the relationship between FinTech and FDI is insignificant, and the effect of FDI on economic performance and SDG achievement is limited, with significance observed only for HFCE and GFCF. However, the most significant finding of this research is the strong and positive effect of FinTech on SDG achievement. Therefore, this study provides a comprehensive understanding of how financial innovation can be leveraged to promote sustainable development and offers evidence-based insights for government policymakers and financial firms to design more effective, context-specific strategies.

CHAPTER 1: INTRODUCTION

1.0 Introduction

This chapter presented an overview of the study, outlining the scope and focus of the research, which examines the intertwined roles of Financial Technology (FinTech) and Foreign Direct Investment (FDI) in driving economic growth and advancing the United Nations' Sustainable Development Goals (SDGs). The discussion is framed by the background of the research and the problem statement, which highlights recent trends and issues arising from the rapid development of FinTech and its interaction with FDI. Building on this foundation, the research questions, objectives, and significance of the study are introduced, emphasizing the need to investigate how FinTech influences the economy through FDI, which is an area that remains relatively underexplored in existing studies.

1.1 Research Background

In recent years, the financial landscape has been significantly altered by the rise of financial technology (FinTech), including distributed ledger technology, digital banking, crowdfunding, electronic money, and mobile money, which has brought about changes in business models across various industries (Choudhary et al., 2025; Mashamba et al., 2023). As FinTech develops, the expansion of financial system resources has narrowed the financial gap of financial exclusion (Choudhary et al., 2025; Sayari et al., 2025). Therefore, Fintech is increasingly recognized as a driver of progress towards macroeconomic growth and sustainable development. For example, the study of Choudhary et al. (2024) shows that Fintech has been shown to positively enhance Gross Domestic Product (GDP), which is a proxy for SDG 8 (Decent Work and Economic Growth).

Given its growing role in the financial sector, a clear understanding of what constitutes FinTech is essential. According to the Financial Stability Board (FSB), FinTech is defined as innovative business models, technical applications, products, and services that will have a significant impact on financial markets and financial services. These innovations are made possible by Big Data, blockchain, cloud computing, artificial intelligence, and other cutting-edge technologies (Xu & Zou, 2022). However, even with its increasing significance, a lack of a generally accepted definition of FinTech still exists due to its multifaceted nature and the diverse proxies and limitations of the Standard Industrial Classification (SIC) code for FinTech (Ochirova & Miriakov, 2025).

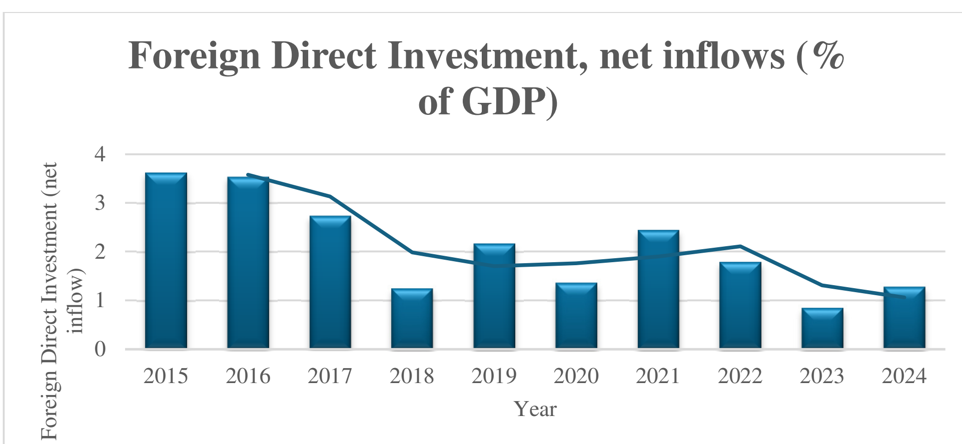
Following the revolutionary development of financial technology, the industry has now entered the FinTech 4.0 era, spanning from 2018 to the present. The latest and current phase of FinTech is primarily driven by disruptive innovations that have led to key advancements, such as Neobanks (Digital Banks), Decentralized Finance (DeFi), Non-Fungible Tokens (NFTs), Artificial Intelligence (AI), and others (Jafri et al., 2025). The FinTech 4.0 is also marked by the rise of scale in the platformization of finance. In this stage of revolution, it involved the disruptive entry of Big Firms, for example, Meta, Apple, Google, and Microsoft globally, further scaling the existing Big Finance incumbents and new FinTechs and TechFins (Buckley et al., 2022). With the leverage of network effects and economies of scope and scale, the market share, data pools, revenue, and profitability of these entities have been maximized (Buckley et al., 2022).

Notably, the COVID-19 pandemic has been identified as a catalyst for the peak era of financial technology globally, according to the study by Liu & Chu (2024). The mobility limitation during that time period strengthened the shift toward contactless payments, digital banking, and decentralized finance (DeFi), accelerating the expansion of digital markets and influencing consumer behavior (Liu & Chu, 2024). Specifically, FinTech had a greater beneficial impact on economic growth, especially in nations with strong internet usage, which helped to lessen the economic downturn (Liu & Chu, 2024). With this evolution, FinTech has expanded its influence into new areas such as

InsurTech, RegTech, and Blockchain (Jafri et al., 2025). This demonstrates that FinTech not only reshapes the traditional financial industry but also extends its reach by creating opportunities across other sectors.

Parallel to the evolution of the financial industry, foreign direct investment (FDI) inflows also play a crucial role in bridging the financing gap and are commonly associated with both short and long-term economic growth (Rodríguez-Chávez et al., 2024). Within the financial sector specifically, there is an increment trend of FinTech innovations in facilitating FDI in technologies, aimed at improving environmental efficiency, often supported by legal frameworks that encourage sustainable development (Sayari et al., 2025). This implies that FinTech not only supports financial modernization but also enhances the attractiveness of a country to cross-border investors by providing scalable solutions. Moreover, FDI inflow often results in job creation, infrastructure development, capital accumulation, and technology transfer, which are particularly essential in developing nations (Rodríguez-Chávez et al., 2024). For instance, it has been demonstrated that Chinese Outward FDI (OFDI) stimulates economic growth by creating jobs and encouraging the development of green technologies (Zhang et al., 2024).

Figure 1.1: Foreign Direct Investment, net inflows (% of GDP)



Sources: World Bank, World Development Indicators (2023)

Nonetheless, according to the UNCTAD report (2025), global FDI flows in 2024 reached US$1.4 trillion, representing an 11% increase from 2023. However, if flows through European conduit economies such as Luxembourg, Ireland, the Netherlands, Switzerland, and the UK are excluded, FDI in 2024 fell by almost 8%. It further highlights contemporary trends in FDI, showing a diverse and complex global environment with notable regional and sectoral variations driven by technological, geopolitical, and economic factors (UNCTAD, 2025). Overall, the service sector is the largest recipient of the greenfield investment project, with $656 billion in value by 2024. This trend aligns with findings showing foreign direct investment is shifting more toward the services sector, which is particularly advantageous for larger developing nations (Rodríguez-Chávez et al., 2024). Within the services sector, financial and insurance cross-border M&A revenues rose sharply by 160%, reaching $33 billion in 2024. Another rapid growth area, the ICT sector, as the related greenfield projects nearly double to $201 billion, led by data center and data processing investments. These developments further highlight the growing potential of fintech and digital infrastructure as key drivers of global FDI flows.

On the other hand, FDI is highlighted as another critical component to bridging the financing gap of the SDGs, particularly in least developed countries, with the projects that are in line with national and regional sustainable development objectives (Rodríguez-Chávez et al., 2024). However, the impact of FDI on SDGs is complex and mixed, especially in the context of social and environmental dimensions (Rodríguez-Chávez et al., 2024; Uddin et al., 2024; Zhang et al., 2024). The mixed outcomes are further complicated by the global economy, which has undergone significant changes and faced numerous challenges, including the slowdown in economic growth following the global financial crisis and, more recently, the COVID-19 pandemic, policy uncertainty amid U.S.-China trade and technology wars. These challenges underscore the urgent need for robust economic growth and the achievement of the United Nations' Sustainable Development Goals (SDGs), particularly highlighted by the UN 2030 Agenda (Rahman et al., 2025). Against this backdrop, this study examines the direct and indirect relationships between FinTech development, economic growth, and the SDGs, using FDI as a mediating variable. By exploring these interconnected pathways, this study aims to gain a more comprehensive understanding of how financial innovation can be strategically leveraged to promote economic performance and sustainable development.

1.2 Problem Statement

Globally, the pursuit of sustainable economic growth and achieving the SDGs are crucial priorities for countries around the world. It is essential, with its goal to ensure that no one is left behind, while simultaneously protecting the planet, promoting economic growth, and prosperity (World Health Organization, 2022). In this context, FinTech and FDI are increasingly recognized as key drivers of sustainable development, given their demonstrated potential to facilitate capital accumulation, enable technology transfer, enhance financial services, and improve financial inclusion (Alvarado et al., 2017; Mahemba & Odhiambo, 2016; Liu & Chu, 2024; Ochirova & Miriakov, 2025). However, existing research largely relies on limited indicators to measure FinTech, such as mobile phone penetration, the number of startups, and credit flows from FinTech firms (Choudhary et al., 2025; Rahman et al., 2025). While useful, these may overlook other critical dimensions of FinTech innovation and development.

Despite the growing interest in FinTech and FDI as tools for development, limited research has examined how FinTech development indirectly advances the economic performance and SDGs with FDI as a mediating role. Existing studies focus more on the separate effects, for example, the direct effect of FinTech on economic performance and individual SDGs (Choudhary et al., 2025; Rahman et al., 2025; Ochirova & Miriakov, 2025) and the direct effect of FDI on economic performance and individual SDGs (Alvarado et al., 2017; Carbonell et al., 2018; Rodríguez-Chávez et al., 2024; Zhang et al., 2024). However, studies have revealed that there is a robust positive correlation between financial inclusion and FDI inflow (Al-Smadi et al., 2024), underscoring the critical role of Fintech as the driver in attracting foreign investment through financial inclusion, including access, availability, and usage. On the contrary, there is also the study of Uddin et al. (2024) has demonstrated a negative impact on environmental efficiency in G20 nations with the combination effect of FinTech investment and FDI. Therefore, the mixed results raised concerns regarding the effectiveness of both FinTech development and FDI in directly and indirectly driving economic growth and sustainable development outcomes.

Focusing on FDI, it has long been acknowledged as a crucial source of funding and a channel for economic growth and global market integration. FDI and its function are also seen as essential to supporting sustainable development, especially in poor countries, since it may fill in financial gaps (An et al., 2025). However, the effectiveness of FDI in promoting economic growth varies greatly throughout economies with varying income levels, and the results are mostly inconsistent from past studies. Research indicates that the impact of FDI can be adverse and statistically significant in lower-middle-income nations, uneven or non-significant in upper-middle-income countries, and favorable in high-income countries (Alvarado et al., 2017; Xu et al., 2024). While several studies (An et al., 2025; Rodríguez-Chávez et al., 2024) have reported a positive impact of FDI on economic growth. Other research suggests that FDI may have no effect or even negative consequences, particularly in countries with low levels of financial development (Azman-Saini et al., 2010; Mahembe & Odhiambo, 2016; Mahmoodi & Mahmoodi, 2016; Alvarado et al., 2017; Carbonell & Werner, 2018). These discrepancies are frequently ascribed to disparities in the absorptive capacity of the host nations, particularly those related to technology absorption capacities, financial market development, and human capital (Alvardo et al., 2017; Rodríguez-Chávez et al., 2024). Given these mixed findings, it is imperative to examine FDI through income-level disparities, which can offer clearer insight into its role in economic growth and SDG attainment across diverse economies.

In the context of the SDGs, existing studies on the influence of FinTech and FDI on various SDGs are largely separate, with a focus on economic growth and environmental dimensions (Choudhary et al., 2025; An et al., 2025; Uddin et al., 2024). In terms of SDGs related to economic dimensions, the relationship with FDI is more consistently positive, with evidence of upward trends in relevant indicators (Rodríguez-Chávez et al., 2024; Xu et al., 2024). For example, FDI can contribute to reducing income inequality through generating job opportunities, but in the long run, it will have the opposite effect on income equality because the income gap widens over time, especially the income gap between urban and rural people (Rodríguez-Chávez et al., 2024). As governance aims to ensure economic stability and sustainable growth, the economic dimension indirectly highlights that existing regulatory frameworks are often insufficient to address the risks and opportunities arising from the increasing scale and concentration of digital finance (Buckley et al., 2022). For the environmental dimensions, FinTech has also been increasingly recognized as a key driver for sustainable finance, such as the function of FinTech in the reduction of CO2 emissions (Rahman et al.,2025) and positive impact on renewable energy consumption (Croutzet & Dabbous, 2021). However, for the social dimensions of sustainable development, such as poverty reduction, healthcare, and labor rights, it remains significantly underexplored, particularly in relation to FDI (Rodríguez-Chávez et al., 2024).

Moreover, the majority of existing studies tend to analyze the relationship of FinTech and FDI with the SDGs in isolation, often emphasizing their impact on a individual goal rather than exploring their combined or cross-cutting effects. Specifically, prior research has linked FinTech with SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-being), SDG 4 (Quality Education), SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 13 (Climate Action) (Choudhary et al., 2025; Liu & Chu, 2024; Rahman et al., 2025; Uddin et al., 2024; Zhang et al., 2024; Sayari et al., 2025). For FDI, the focus has been largely on SDG 8, SDG 9, and SDG 13 (Xu et al., 2024; Rodríguez-Chávez et al., 2024; An et al., 2025; Satyanand, 2021; Zhang et al., 2024) This indicates a lack of studies addressing other relevant SDGs, as well as a limited exploration of the interconnected relationship between FinTech and FDI in advancing the SDGs. Therefore, further research is needed on how FinTech and FDI jointly impact the SDGs, especially beyond those that have been thoroughly studied previously. Nonetheless, there is also sparse research on FinTech and FDI with the overall SDGs impact. Therefore, there is a need to incorporate the overall SDG index to capture a comprehensive measure of sustainable development performance, enabling this study to assess the aggregate impact of FinTech and FDI on a country’s advancement across economic, social, and environmental dimensions.

1.3 Research Questions

Following the problem statement, the issue of limited indicators for measuring FinTech needs to be addressed, highlighting the importance of incorporating more critical dimensions into the assessment. Additionally, income level significantly moderates how FinTech operates due to differences in infrastructure, financial ecosystems, human capital, and regulatory frameworks (Alvarado et al., 2017). These issues and limitations lead to the following research question, which incorporates broader FinTech indicators and applies income-level classifications:

RQ1: What are the differences in FinTech development among low-income, lower-middle-income, upper-middle-income, and high-income economies?

As noted in the problem statement, the relationship between FinTech and FDI remains empirically mixed, highlighting the need to further investigate how FinTech development influences FDI across income-diverse contexts. This leads to the second research question:

RQ2: How does FinTech development impact Foreign Direct Investment (FDI) across economies with different income levels?

Given that FDI's impact is inconsistent across economies with different income levels and its contribution to sustainable economic growth varies (Alvarado et al., 2017; Xu et al., 2024), further analysis is needed of its direct impact on macroeconomic outcomes. Furthermore, as FinTech develops, its impact on FDI may become an indirect channel through which it influences economic performance. These considerations raise the following research questions:

RQ3: How does Foreign Direct Investment (FDI) directly impact macroeconomic performance, including Households and NPISH Final Consumption Expenditure (HFCE)*, GDP Growth, Unemployment Rate, Gross Fixed Capital Formation, and Carbon (CO2) emissions?*

RQ4: How does FinTech development influence macroeconomic performance, including Households and NPISH Final Consumption Expenditure (HFCE*), GDP Growth, Unemployment Rate, Gross Fixed Capital Formation, and Carbon (CO2) emissions through the mediating role of Foreign Direct Investment (FDI)?*

Beyond macroeconomic indicators, both FDI and FinTech are increasingly linked to broader sustainable development outcomes. As highlighted in the problem statement, the mixed findings regarding their impact on individual SDGs, and the lack of research using the overall SDG Index. It underscores the need to investigate their relationship with sustainable development more holistically. This leads to the final research questions:

RQ5: How does Foreign Direct Investment (FDI) directly impact the achievement of SDGs?

RQ6: How does FinTech development influence the achievement of SDGs through the mediating role of Foreign Direct Investment (FDI)?

1.4 Research Objectives

Based on the research question, the general objective of this study is to examine the differences in FinTech development across economies with varying income levels. This research aims to provide a clearer understanding of the current status, growth potential, and overall development of the FinTech industry.

RO1: To compare FinTech development trends among low-income, lower-middle-income, upper-middle-income, and high-income economies.

Building on the general objective and the first research objective, additional objectives are formulated to provide a deeper understanding of the interconnections between FinTech development, FDI economic performance, and the achievement of the SDGs. These goals seek to encompass the broader implications of FinTech and FDI for sustainable economic growth, as well as their direct and indirect effects. Therefore, the following research objectives have been set:

RO2: To examine the impact of FinTech development on Foreign Direct Investment (FDI) across economies with different income levels.

RO3: To examine the direct impact of Foreign Direct Investment (FDI) on macroeconomic performance, including Households and NPISH Final Consumption Expenditure (HFCE), GDP Growth, Unemployment Rate, Gross Fixed Capital Formation, and Carbon (CO2) emissions.

RO4: To examine the direct and indirect impact of FinTech development on macroeconomic performance, including Households and NPISH Final Consumption Expenditure (HFCE), GDP Growth, Unemployment Rate, Gross Fixed Capital Formation, and Carbon (CO2) emissions through the mediating role of Foreign Direct Investment (FDI)

RO5: To examine the direct impact of Foreign Direct Investment (FDI) on the achievement of SDGs

RO6: To examine the direct and indirect impact of FinTech development on the achievement of SDGs through the mediating role of Foreign Direct Investment (FDI)

1.5 Significance of the Study

The study's significance is multifaceted, offering crucial insights for various stakeholders involved in foreign FDI, FinTech, and sustainable development. By examining the role of FinTech development and FDI in shaping macroeconomic outcomes and sustainable development across countries with varying income, the study addresses critical gaps in existing literature. Its comprehensive approach contributes both theoretically and empirically, offering practical, evidence-based recommendations.

1.5.1 Government and Policymakers

The scope of the study that understands the effectiveness of Fintech and FDI influence economic growth, and SDGs can provide the insight and guidance that governments and policymakers in design more effective and context-specific economic and development strategies. As one of the objectives of the study, this research directly addresses the inconsistency of FDI's impact on different income levels. Through the understanding of the FDI's heterogeneous impact, the government can apply the strategy by avoiding a "one-size-fits-all" strategy and instead executing focused policies that promote economic growth. Additionally, identifying the potential growth of the FinTech sector highlights that policymakers should prioritize support and allocate resources toward developing robust FinTech infrastructure and clear regulatory frameworks. By transforming the traditional financial system, a well-developed FinTech sector can attract more FDI, stimulate economic growth, and accelerate the achievement of SDGs for long-term sustainability. Furthermore, by classifying countries by income level, the study offers region-specific insights that can inform targeted investment strategies and reveal how FinTech and FDI function across diverse economic environments.

1.5.2 International Organizations

International organizations, including the United Nations, the World Bank, and the International Monetary Fund (IMF), play a critical role in supporting the achievement of the SDGs, promoting digital inclusion, and facilitating global investment. The findings of this research offer valuable evidence on how FinTech and FDI can jointly contribute to a broader and more integrated set of sustainable development outcomes. These insights can inform the development of standardized metrics, best practices, and policy guidelines aligned with the UN 2030 Agenda. Moreover, by highlighting the complex interdependence between FinTech, FDI, economic growth, and SDG attainment, this study supports the formulation of more effective and coordinated global strategies. The cross-country, income-level-based analysis also provides a replicable model for generating broader perspectives and more generalizable conclusions across different economic contexts.

1.5.3 Traditional Financial Institutions and FinTech Firms

This study can offer strategic value to both traditional financial institutions and FinTech firms, particularly in terms of competitive dynamics and opportunities within the broader economic and sustainable development landscape. Traditional banks can use the findings to adapt to rapidly evolving financial environments and technological disruption. Digital transformation, for instance, may serve as a key strategy for traditional institutions to remain competitive in response to the growth of FinTech innovation and changing market demands. The results may also support efforts to integrate core FinTech technologies, enabling banks to offer more innovative services and strengthen their market positions by providing financial products to MNCs that carry out FDI in their country.

For FinTech companies, the study provides insights that can support the identification of growth opportunities, attract investment, and align technological innovation with broader development goals. By analyzing the relationship between FinTech and FDI, the research highlights strategic pathways for international expansion, particularly by positioning FDI as a viable mode of market entry, rather than relying solely on cross-border service provision. Additionally, the findings shed light on regional differences in the adoption of financial services, revealing untapped opportunities in underdeveloped markets where FinTech can offer scalable and inclusive solutions.

1.6 Chapter Summary

In short, the main purpose of this study is to examine the interconnected roles of FinTech and FDI in promoting economic growth and achieving the United Nations' SDGs. The increasing growth of the FinTech industry, driven by innovations such as digital banking, mobile money, and decentralized finance, has reshaped the financial landscape by expanding inclusion and accelerating digital adoption, particularly during the COVID-19 pandemic. At the same time, FDI also plays an equally important role in bridging financing gaps, creating jobs, and supporting technology transfer, with the services sector, especially ICT and financial services. While FDI's contribution to growth shows variation across income levels, the combined effects of FinTech and FDI remain underexplored.

At the same time, FinTech and FDI are highly recognized as critical components for achieving the SDGs. However, their impact is complex and can be mixed, especially concerning social and environmental dimensions. Mostly, however, existing studies reveal inconsistent findings, limited research scope, and measurement issues in examining how FinTech and FDI interact, especially in relation to economic performance and long-term development outcomes. To address these gaps, the study investigates income-level differences in FinTech development, the role of FinTech in attracting FDI, and the direct and indirect impacts of both FinTech and FDI on macroeconomic indicators and SDG progress.

On top of that, the findings are expected to offer valuable insights for several stakeholders, which are Governments and Policymakers, International organizations, and Financial and FinTech firms. Specifically, the insight of this research can help in designing more effective, context-specific policies and strategies for both FDI and FinTech-related sectors. It can also raise the awareness of these international organizations in developing standardized frameworks for leveraging FinTech and FDI. Meanwhile, this study will also provide strategic insights into market opportunities, competitive dynamics, and pathways for international expansion, helping traditional banks adapt and FinTech firms align their innovations with development goals.

1.7 Chapters Layout for this Research

This report is organized into five chapters: Introduction, Literature Review, Methodology, Results and Discussion, and Conclusion.

Chapter 1: This chapter includes the research background, problem statement, research questions, and research objectives, which collectively reveal the scope and provide an overview of this study.

Chapter 2: This chapter presents the literature review, which consists of theoretical reviews to support the analysis. In addition, it covers the review of variables and past studies. Building on these, the conceptual framework and hypotheses are developed.

Chapter 3: This chapter explains the methodology employed in this research, including the research design, sampling design, measurement of variables, data collection procedures, and the statistical techniques and tests used for analysis.

Chapter 4: This chapter presents the results derived from the statistical techniques and tests, followed by a detailed discussion of the findings with reference to the study's hypotheses.

Chapter 5: This chapter provides a summary of the key findings, implications, and limitations of this research. It also outlines the study's limitations and provides recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter establishes the theoretical and empirical foundations for investigating the relationships between FinTech development, FDI economic performance, and the achievement of SDGs. Specifically, it includes the key theories that offer competing perspectives on these complex interactions between the variables. To identify the recent trends, relationships, and research gaps, a comprehensive review of the past studies is presented in this chapter. It further highlights the areas where evidence is mixed or inconclusive. Building on a review of theories and past studies, the chapter develops a conceptual framework to structure the analysis and outlines a set of detailed hypotheses that will be tested to generate meaningful insights into how FinTech and FDI influence economic performance and sustainable development outcomes.

2.1 Review of Theoretical Framework/ Theories

2.1.1 The Influence of FinTech development on FDI

In examining the influence of FinTech development on FDI, there is a lack of direct theory that is built based on this relationship, but there are several well-established theories that can help explain the findings of existing studies. However, given the complexity of the market, multiple perspectives and arguments have emerged regarding this relationship. To provide a theoretical foundation before presenting the research results, this section highlights two key frameworks, which are International Investment Location Theory and Institutional Theory.

2.1.1.1 International Investment Location Theory (Jiang et al., 2024)

The foundations of the International Investment Location Theory were primarily established by John H. Dunning and subsequently expanded by other economists and scholars. In relation to the influence of FinTech development on FDI, the most relevant framework within this theory is the eclectic paradigm of international production, as outlined in the study of Dunning (1988). According to the eclectic paradigm, international production, closely related to FDI, is determined by the OLI framework, which consists of ownership-specific advantages, locational advantages, and internalization advantages. Focusing on locational advantages, the study has emphasized that Multinational Enterprises (MNEs) are attracted to the locations that offer favorable factor endowments, such as natural resources, a specific type of labor, and large and growing markets. It also argues that the concept of the MNEs is inclined to invest in regions with well-developed financial systems. Additionally, both structural and transactional market failures will also affect the FDI decisions. For instance, structural market distortions, such as tariffs, trade barriers, will influence the attractiveness of the country as a location to be invested in. At the same time, transactional market factors, such as enhanced arbitrage opportunities, reduced exchange rate risk, and improved coordination of financial decisions, can provide additional benefits that affect the locational determinants of FDI (Dunning, 1988).

Building on this theory, the FinTech development that affects a country's financial system is expected to be one of the key factors in altering a country's locational advantages. This is because FinTech, which includes digital finance, can enhance the advantages in ways that a transitional financial system is unable to achieve. For example, FinTech development can enhance financial accessibility through digitalizing the financial services, and further expand the breadth of financial inclusion. Other than that, it can also increase efficiency, especially in the capital allocation of the financial markets. Both of these can reduce the financial friction and transaction cost, which can make the markets more attractive to foreign investors. Moreover, FinTech fosters innovation by easing financing constraints for start-ups and SMEs, thereby stimulating real economic growth. These combined effects strengthen a country's financial infrastructure and improve its competitiveness as an investment location, suggesting that FinTech development positively influences FDI inflows.

2.1.1.2 Institutional Theory / Financial Development Theory

Institutional Theory was first proposed by John W. Meyer and Brian Rowan in 1977, and further developed by Paul J. DiMaggio and Walter W. Powell in 1983 through the concept of institutional isomorphism. This theory primarily discusses the emergence of formal organizational structures as a reflection of rationalized institutional rules. In the paper of Meyer and Rowan (1977), they emphasized that organizational practices and processes are frequently adopted not only for their immediate technological efficacy, but is because of the need for legitimacy, stability, and survival in a highly institutionalized environment. It suggests that organizations may adopt new practices primarily for survival prospects and legitimacy rather than efficiency, thereby presenting themselves as appropriate, rational, and modern. Building on this foundation, Paul J. DiMaggio and Walter W. Powell then further developed the concept into coercive isomorphism, mimetic isomorphism, and normative isomorphism. It suggests that the adoption of the policies of perceived leaders, which leads to the imitation of organizations, is highly due to global pressure and uncertainty, rather than local readiness. Additionally, the study also emphasized that organizations are often rewarded for being similar to others, as this facilitates transactions, attracts staff, and enhances legitimacy. However, if the broader organizational field is based on flawed or superficial models, such similarity provides little real advantage and may even heighten risk.

Applying this theory to the FinTech industry, it would be argued that the growth and application of FinTech in countries is due to the global pressure, survival, uncertainty and etc. In this case, the FinTech policies may be more symbolic compliance, which makes the organization look modern and legitimate, rather than improving financial efficiency. With this, if the FinTech reforms are poorly implemented, it may not increase the foreign investors' confidence. On the contrary, investors may become wary of a region where all countries have adopted the same trendy but untested policies. Due to the indirect effect that can be examined by this theory, it can be predicted that the relationship between FinTech and FDI is highly conditional and potentially negative. Additionally, the facts of the FDI flow are highly dependent on a country's local conditions and absorptive capacity, which may further affect the development of FinTech and the restriction of the FDI flow. It further highlighted that the relationship is not direct and might differ across countries and regions.

2.1.2 The Influence of FinTech development on Economic Performance

Due to the emerging growth of FinTech development, particularly at the peak of the COVID-19 pandemic, the prior studies have widely explored the relationship between FinTech and financial development on economic performance. With the rapid development and changes of the financial industry, there is multiple theories exist; therefore, in this section, the Endogenous Growth Theory and Too Much Finance Hypothesis will be discussed to further understand the complex influence of the FinTech development.

2.1.2.1 Endogenous Growth Theory (EGT) (Xu et al., 2024)

The Endogenous Growth Theory was initially formed by Robert Lucas in 1988, which focuses on human capital and skill level as the driver of growth. In this theory, there is a found linear relationship between effort and human capital growth, which will further lead to sustained per-capita income growth endogenously (Lucas, R.E., 1988). Paul Romer then further developed this concept by highlighting the role of technological changes as the key driver of economic growth, which is able to provide incentives for capital accumulation. In his view, technological changes are endogenous, which primarily stems from deliberate investment decisions made by profit-maximizing entities driven by market incentives. It includes the market-driven actions such as the investment in research and development, innovation, and training. Additionally, the unique characteristics of technology have also been discovered that it is non-rivalry and partial excludability, which further introduce non-convexities into production and allow for increasing returns to scale. (Romer, 1990)

FinTech development, characterized as a vital component of the digital economy, aligns directly with the principles of Endogenous Growth Theory by using innovation and technology to drive and facilitate economic growth. The cutting-edge technologies applied in FinTech, such as AI, Blockchain, and Big Data, indicate their potential to bring about significant technological changes. Building on this theory, it can be predicted that continuous FinTech development may become a primary driver of economic growth. In terms of human capital, FinTech is a growing industry with the capacity to create more job opportunities, which will further enhance human capital. Together, both technology and human capital emphasize the potential of FinTech development to contribute to the growth of economic performance.

2.1.2.2 Too Much Finance Hypothesis (An et al., 2025)

The Too Much Finance Hypothesis was proposed by Jean-Louis Arcand, Enrico Berkes, and Ugo Panizza in an IMF Working Paper (2012). The hypothesis suggests that beyond a certain threshold, financial development no longer exerts a positive effect on economic growth and may instead have a negative impact. Building on this, financial depth and economic growth thus have a non-monotonic, concave, or inverted U-shaped connection. Furthermore, the research results indicate that finance begins to exert a negative effect on economic growth once credit to the private sector reaches a certain threshold of GDP, for example, 83% of GDP (1970–2000), 82% of GDP (1970–2005), and 88% of GDP (1970–2010). At the same time, this hypothesis also further supports the vanishing effect that the positive correlation weakens as the size of the financial sector grows over time (Arcand et al., 2012). The authors suggest that the potential reasons for the detrimental effects on economic growth include increased macroeconomic volatility and crises, as well as the misallocation of resources and talent, which is consistent with the arguments put forward by James Tobin (1984). In the argument, James Tobin highlighted that speculative capital movements and excessive short-term financial flows might cause economic instability and lower productive investment.

Therefore, based on this concept, FinTech development might have a limited or even negative effect on economic growth, depending heavily on a country's stage of economic and regional development. The hypothesis suggests that there is an optimal level of financial sector growth, which is highly relevant to FinTech's role in driving financial innovation and digital transformation. This highlights that the influence of FinTech development on economic performance is uncertain and context-dependent.

2.1.3 The Influence of FinTech development on the achievement of SDGs

With the increasing awareness of the SDGs, the studies that examine the influence of FinTech development on the achievement of SDGs are simultaneously increasing. However, the established framework or theory that was built on the direct effect of this relationship is still underdeveloped. Therefore, based on the existing studies, the well-developed theories, which are Innovation Diffusion Theory and Complex Systems Theory, are suitable for examining this particular relationship from a different perspective, which will be discussed in the following.

2.1.3.1 Innovation Diffusion Theory (Choudhary et al., 2025)

The Innovation Diffusion Theory was developed by Everett M. Rogers in his book Diffusion of Innovations, first published in 1962 and later updated in subsequent editions in 1971, 1983, 1995, and 2003. The core concept focuses on how innovations gradually spread within a social system through specific pathways, while also recognizing that the novelty of new ideas often creates uncertainty for individuals considering adoption. There are four main elements in this theory, which are innovation, communication channels, time, and a social system. An innovation's perceived attributes, such as relative advantage, compatibility, complexity, trialability, and observability, determine its likelihood of adoption. Meanwhile, it suggests the diffusion can occur through mass media or interpersonal channels, which is especially efficient when engaging with close neighbors. In short, over time, adoption moves through stages from awareness to confirmation, and the social structure of the system, opinion leaders, and change agents all have a significant impact on the rate and pattern of diffusion (Rogers, E. M., 1995)

In this context, FinTech, as an advanced innovation in the financial industry, such as mobile banking, digital wallets, and robo-advisors for investment, requires widespread adoption to determine its impact on the achievement of the SDGs. While many SDGs desired outcomes, for example, zero hunger, decent economic growth, and quality education, require specific innovations to be widely adopted. Therefore, the FinTech diffusion facilitates broad access to financial services and speeds up technology adoption by lowering transaction costs and information asymmetry (Choudhary et al., 2025). Through enhanced financial inclusion and adoption, FinTech contributes to the advancement of multiple SDGs, supporting the creation of a more sustainable and inclusive global economy. Additionally, the social systems, communication channels, and perceived innovation attributes provide a framework for understanding why adoption may be slower in low-income contexts, where financial literacy, infrastructure, and economic conditions present additional barriers.

2.1.3.2 Complex Systems Theory

The Complex System Theory has evolved across multiple disciplines, with contributions from several authors, such as Hebert A. Simon, Ludwig von Bertalanffy, Kenneth Boulding, and Richard S. Johnson, among others. As the name implies, a complex system is a system composed of numerous interrelated components that interact with one another in complex, nonlinear ways, rather than operating as separate or independent entities. The core concept of the theory suggests holism, which means the whole is more than the sum of its parts. It emphasized that focusing solely on specialized functions can cause managers to lose sight of the overall goals of the enterprise and their specific business's role in the larger system. Additionally, the theory highlights how complex forms evolve from simpler ones and that the existence of stable intermediate forms is crucial for rapid evolution (Rosenzweig et al., 1972; Simon, 1962; Johnson et al., 1964).

In the context of FinTech, the development or growth of a field that consists of digital financial technologies interacts with various economic, social, and regulatory elements in ways that are complex and context-dependent. Although some studies support that FinTech can increase economic efficiency and financial inclusion (Mahemba & Odhiambo, 2016), its wider effects on the SDGs are not straightforward. Moreover, the interconnected nature of digital finance introduces challenges such as cybersecurity threats, regulatory lag, and systemic vulnerabilities, which may further hinder the achievement of the SDGs. Ultimately, the theory highlights that the influence of FinTech on SDGs remains uncertain and inherently unpredictable.

2.1.4 The Influence of FDI on Economic Performance

In examining the relationship between FDI and economic performance, this connection has been extensively explored by economists and researchers. FDI is widely recognized as a key driver of economic growth; however, the theoretical explanations of this relationship remain mixed, particularly when accounting for differences across nations, income levels, and development stages. To build a stronger foundation for understanding this relationship, the FDI–Growth Spillover Theory and the Absorptive Capacity Hypothesis will be reviewed in the following sections.

2.1.4.1 FDI-Growth Spillover Theory

The FDI–Growth Spillover Theory constitutes a theoretical framework that has been progressively developed and refined by numerous scholars over time. Key contributors to this body of work include Stephen Hymer (1976), Richard Caves (1971), Robert Finlay (1978), and Shoukry Das (1987), among others. The core concept of the theory suggests that relationships and mechanisms through which FDI is expected to contribute to economic growth in host countries, rather than simply capital injection. Economic growth is also often enhanced by spillover effects transmitted through channels such as technology transfer, human capital formation, increased competition and efficiency, capital accumulation, and infrastructure development. Through these spillover effects, the theory suggests that FDI can facilitate domestic technological change, promote income growth, and stimulate R&D in host countries. This process may further contribute to narrowing income gaps (Fan & Asian Development Bank, 2002).

Building on this widely developed theory, FDI is predicted to have a positive influence on economic growth. Through spillovers and externalities, FDI serves as a channel for the transfer of technology, knowledge, and efficiency improvements, thereby enhancing the host country’s overall economic performance. Moreover, based on this theory, FDI can also act as a driver of FinTech development, demonstrating an interconnected relationship in which both FDI and FinTech reinforce each other’s contributions to economic growth.

2.1.4.2 Absorptive Capacity Hypothesis

The Absorptive Capacity Hypothesis is the notable refinement of the FDI Growth Spillover Theory. This theory is proposed by Wesley M. Cohen and Daniel A. Levinthal (1990) in the paper of Absorptive Capacity: A New Perspective on Learning and Innovation. They argue that positive spillovers are not automatic but depend on the host country’s ability to effectively absorb and utilize foreign investment (Cohen & Levinthal, 1990). This hypothesis also explains why the benefits of FDI for economic growth can vary across different host countries and regions. It also further emphasized that the diversity of knowledge within individuals and organizations is particularly significant because it enables new associations and linkages, which are essential for innovation, and improves the possibility that new information will relate to recent advancements (Cohen & Levinthal, 1990)

In the context of this research, the hypothesis highlights that the extent to which countries benefit from FDI differs across regions, depending on their capacity to adopt and utilize these advantages. Consequently, the impact of FDI on economic performance is expected to be mixed and to vary significantly across countries.

2.1.5 The Influence of FDI on the achievement of SDGs

Similarly, as research on FDI has expanded over the decades, theoretical perspectives have also been developed to explain its influence on the achievement of the SDGs, given the interconnected nature of FDI's effects. While no single theory directly addresses the impact of FDI on all SDGs, the same frameworks, which are FDI–Growth Spillover Theory and the Absorptive Capacity Hypothesis, are suitable to provide a strong foundation for examining how FDI contributes to economic, social, and environmental dimensions of sustainable development.

2.1.5.1 FDI-Growth Spillover Theory

As discussed in Section 2.1.4.1, FDI-Growth Spillover Theory, this is also applicable to the influence of FDI on the achievement of SDGs. The theory positions FDI as a driver of the achievement of SDGs, especially in terms of economic, social, and environmental (Rodríguez-Chávez et al., 2024). For example, spillovers from FDI through technology transfer and infrastructure development directly support SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure). In addition, the innovation and growth stimulated by FDI can further advance SDG 10 (Reduced Inequalities) by generating employment opportunities and facilitating technological progress that reduces information asymmetries. Moreover, as FDI-driven growth increases the demand for skilled labor and technological expertise, host countries are incentivized to invest more in education and skills upgrading, thereby reinforcing SDG 4 (Quality Education).

2.1.5.2 Absorptive Capacity Hypothesis

Similarly, building on the Absorptive Capacity Hypothesis discussed in Section 2.1.4.2, while the FDI–Growth Spillover Theory highlights the positive influence of FDI, this hypothesis further refines the argument by emphasizing that the extent to which host countries benefit from FDI spillovers largely depends on their absorptive capacity. In this context, the UN 2030 Agenda reinforces the hypothesis by recognizing FDI as a crucial instrument for bridging the financial gap in achieving the SDGs. However, the effectiveness of FDI in this regard depends on the alignment of investment projects with national and regional sustainable development strategies, which in turn requires sufficient absorptive capacity in terms of planning, governance, and institutional frameworks. It further highlighted and explained why the impact of FDI on the achievement of SDGs varies significantly across countries.

2.2 Review of Constructs/ Variables

2.2.1 FinTech Development

In general, FinTech development refers to the measurable expansion and adoption of financial technology products and services. It represents a major transformative force within the global financial ecosystem, reshaping business models, market dynamics, and the delivery of financial services (Warokka et al., 2025; Kostov et al., 2025; Jafri et al., 2025). According to the Financial Stability Board (FSB), FinTech is used to defined as the application of innovative technologies and business models that significantly impact traditional financial markets and services. The cutting-edge technologies or innovations include AI, Blockchain, Big Data, and Cloud Computing, to provide more creative, practical, and efficient financial solutions (Xu & Zou, 2022).

Due to the multifaceted nature of FinTech, there is a lack of standardized measurement of FinTech development. Instead, various indicators are employed to capture its different dimensions, such as the FinTech market, efficiency, access, etc. In the prior studies, the commonly used measurements include a composite index to capture more dimensions simultaneously. For instance, the Financial Development Index from the IMF (An et al., 2025), which primarily measures the development across depth, access, and efficiency dimensions. Similarly, the Financial Inclusion Index, constructed using Principal Component Analysis (PCA) based on access and usage indicators of financial services, has also been applied in empirical research (Choudhary et al., 2025). Other composite indices used in the existing studies included the Digital Connectedness Index (Kostov et al., 2025), the Peking University Digital Financial Inclusion Index (Lee et al., 2024), the Ranking of Fintech development in the Institute for Financial Service Zug (IFZ), and Listing in the FinTech Hub Ranking (Liu & Chu, 2024)

In addition, prior studies have also employed single-dimensional measures of FinTech development when addressing targeted aspects of financial innovation. Existing studies employed the number of FinTech companies and start-ups as the measurement of FinTech development the most, to indicate the market activity, appeal, and entrepreneurial vibrancy (Lee et al., 2024; Warokka et al., 2025; Xu et al., 2024; Kostov et al., 2025). The other measurements that are relevant to the activity of FinTech companies include FinTech-based credit flows (Choudhary et al., 2025; Rahman et al., 2025), the total registered capital amount of FinTech companies (Lee et al., 2024), and FinTech mergers and acquisitions deals (Ochirova & Miriakov, 2025).

On the other hand, another key indicator of FinTech development and diffusion that existing studies employed is mobile phone penetration and subscription. It is used to indicate the capabilities and access of mobile technology, which will further influence the utilization of FinTech services (Choudhary et al., 2025; Mashamba et al., 2023). In addition, to capture FinTech development from the perspective of technological adoption and infrastructure, prior studies have employed indicators such as internet usage (Sayari et al., 2025; Xu et al., 2024), digital payments (Choudhary et al., 2025), digital currency usage, peer-to-peer lending, and ICT exports (Sayari et al., 2025). Besides, some studies have used indicators such as FDI in FinTech to capture funding and investment in the sector (Kostov et al., 2025; Uddin et al., 2024).

2.2.2 Foreign Direct Investment (FDI)

FDI refers to cross-border investment made by an individual, organization, or government from one country into the commercial activities of another (Davies et al., 2024). It typically involves acquiring a substantial and lasting interest, often through ownership or managerial control over a foreign entity (Al-Smadi & Al-Smadi, 2024). According to the OECD benchmark definition, FDI is characterized by the investor holding at least 10% of the voting power, ensuring significant influence or control over the management of the business (Davies et al., 2024). Additionally, FDI can take various forms, including joint ventures, mergers and acquisitions, and the establishment of new projects.

Owing to the growing body of research on FDI, the measurement of foreign direct investment has become increasingly standardized. In prior studies, the most widely used measurement of FDI is the FDI net inflows as a percentage of Gross Domestic Product (GDP), which is typically sourced from the World Bank (An et al, 2025; Azman-Saini, Baharumshah, & Law, 2010; Xu et al., 2024; Al-Smadi & Al-Smadi, 2024). Furthermore, some studies also use the total stock of FDI or the cumulative total of nominal FDI inflows as a proxy for FDI. (Bermejo Carbonell & Werner, 2018). As additional information, in the context of FinTech, FDI is often measured using specific investment indicators such as the total capital investment (in USD millions) and the number of jobs created on a monthly basis, derived from project-level data sources such as FDI Markets (Kostov et al., 2025).

2.2.3 Economic Performance

Economic performance refers to the overall health, development, and effectiveness of the economy of the country (Choudhary et al., 2025; Steil et al., 2021). It generally encompasses elements such as output growth, capital accumulation, and job creation, which in turn influence national income, living standards, and overall economic welfare (Alvarado et al., 2017; Steil et al., 2021). In other words, economic performance also reflects a country's ability to generate wealth, attract investment, and transform innovation into growth, while being influenced by additional factors such as the quality of institutions and government policies (Steil et al., 2021; Azman-Saini et al., 2010).

In terms of measurement, economic performance involves various focus of dimensions with specific indicators. The most widely used measure in existing studies is Gross Domestic Product (GDP), which can be expressed in different forms, such as real GDP and GDP per capita (Alvarado et al., 2017; Azman-Saini et al., 2010; Mahemba & Odhiambo, 2016; Choudhary et al., 2025; An et al., 2025; Warokka et al., 2025). GDP is a crucial economic indicator, as it reflects the overall growth and development of a country's economy. Similar to GDP growth, Gross National Income (GNI) per capita, which reflects the average income of individuals, is commonly used to indicate improvements in living standards (Sayari et al., 2025).

Furthermore, in relation to FinTech and FDI, the Human Development Index (HDI) is often employed as a crucial indicator to capture achievements in health, education, and standards of living, particularly within the broader context of socio-economic development (Sayari et al., 2025; Warokka et al., 2025). Other studies have also employed indicators such as the unemployment rate and human capital, where employment and job creation are seen as direct economic benefits linked to FDI inflows and overall economic performance (Al-Smadi & Al-Smadi, 2024; Rodríguez-Chávez et al., 2024; Uddin et al., 2024). Besides, existing studies that focused on the study of economic performance with financial innovation often employed measurements like household consumption expenditure, General government final consumption expenditure, and the growth rate of household consumption to reflect the government and consumer spending in a certain field. (Ochiro et al., 2025; Luo, Sun, & Zhou, 2022; An et al., 2025)

In addition, the indicators like investment ratio, gross fixed capital formation are also frequently used to reflect economic growth due to their ability to reflect investment in productive assets. (Azman-Saini, 2010; Alvarado et al., 2017; Choudhary et al., 2025). For another perspective, the most widely used measure of income inequality within a country that arises from the different levels of growth of the economies is the Gini coefficient, which ranges from 0-100 (Demir et al., 2022). Other studies have also employed measurements like carbon dioxide (CO2) emissions as an indicator for a green economy, with a high mixed results in relation to FDI (Uddin et al., 2024; Rahman et al., 2025). Additionally, some studies have also employed additional indicators such as capital formation, financial market volatility, infrastructure development, and institutional quality for the evaluation of economic performance.

2.2.4 Sustainable Development Goals (SDGs)

Sustainable Development Goals are a series of aspirational but doable global goals that were developed in the UN's 2030 Agenda. In detail, there are a total of 17 SDGs outlined as a shared blueprint (United Nations, 2025). These outlined goals aim to address important issues facing global progress, encourage sustainable development, and advance the general improvement of people, communities, and the environment (Buckley et al., 2022; Rodríguez-Chávez et al., 2024).

In the context of FinTech and FDI, various specific goals have been examined in the existing studies due to their interconnectedness to economic, social, and environmental development. Specifically, relevant to economic dimensions, existing studies have employed relevant SDGs, which are SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 10 (Reduced Inequality) as the indicators. (Choudhary et al., 2025; Salleh et al., 2025). This focus reflects the potential of FinTech and FDI to stimulate innovation, thereby enhancing economic growth and contributing to the reduction of inequality.

For the social dimensions, prior studies have also used SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-being), and SDG 4 (Quality Education) as the specific measurement that relates to FinTech (Choudhary et al., 2025). These SDGs are particularly important because fintech can improve financial inclusion, make it easier for people to access necessary services, and foster the growth of human capital. All of these have direct impacts on food security, healthcare, and education outcomes.

Moreover, SDG 13 (Climate Action) has also been examined in existing studies as an environmental dimension related to FinTech and FDI (Rahman et al., 2025; Uddin et al., 2024; Zhang et al., 2024). These studies have emphasized that FinTech has potential for resource management, green finance, and climate change adaptation and mitigation (Rahman et al., 2025). FDI can also facilitate the transfer of green technologies, which in turn can positively influence environmental sustainability (Uddin et al., 2024).

2.2.5 Income Level

In terms of moderating indicators, income level is often employed as a key variable. In studies examining the relationship between FinTech, FDI, economic performance, and the SDGs, countries are frequently categorized by income level to assess how the impacts of FinTech and FDI differ across various stages of economic development.

The most common methodology for categorizing income levels in existing studies is the World Bank's Atlas Method, which classifies countries based on national income per capita (Alvarado et al., 2017; An et al., 2025; Choudhary et al., 2025; Mahemba & Odhiambo, 2016). Specifically, countries are grouped into four categories: high-income, upper-middle-income, lower-middle-income, and low-income economies. The studies have also emphasized that income level often correlates with absorptive capacity, institutional quality, and financial development (Alvarado et al., 2017). The frequent use of income level as an indicator highlights its significance in shaping both the nature and strength of the relationships between relevant factors and various development outcomes.

2.3 Review of Past Studies

2.3.1 The Influence of FinTech development on FDI

Despite growing interest in FinTech, studies explicitly addressing its direct influence of FinTech development on FDI remain limited. This represents a critical gap, considering the multifaceted role of FinTech in shaping global economic activity, financial stability, policymaking, and sustainable development. On the whole, existing research on the relationship between

FinTech development and FDI and related financial flows offers mixed evidence, reflecting diverse methodological approaches and regional focuses.

In detail, existing studies have identified the direct influence of FinTech development on FDI, as evidenced by Jiang et al. (2024), Kostov et al. (2025), and Satyanand (2021). In particular, the study of Jiang et al. (2024), which used panel data analysis at the 279 prefectural level in China from 2011-2019, highlights that digital finance, empowered by FinTech, exerts a positive net effect on FDI, with a more pronounced complementary effect than a substitution effect. In the particular study, it has also highlighted the influence operates through two main channels, which are the financial effect and economic effect. Similarly, Kostov et al. (2025), applying econometric modeling and state-space regressions to UK–India data from 2011 to 2021, reported that FinTech-driven FDI increasingly substitutes traditional trade in financial services. For India specifically, both the 'Size of FinTech' ($\beta = 0.010$, SE = 0.004) and 'FinTech Funding' ($\beta = 0.009$, SE = 0.002) significantly enhanced capital investment.

Moreover, Satyanand (2021), drawing on the World Economic Forum (WEF) survey of 310 global tech firms and UNCTAD surveys of Investment Promotion Agencies (IPAs), highlights that factors such as ease of obtaining licenses, data security regulations, and the availability of e-payment systems play an important role in attracting FDI. The study further notes that progress in these areas can generate employment opportunities, facilitate technology transfer, and support broader economic development. Additionally, there is also a finding that highlights a significant and positive relationship between indirect factors, which are financial inclusion and FDI inflows in the Middle East and North Africa, which is the MENA region, over the 2003-2022 period (Al-Smadi & Al-Smadi, 2024). The study of Al-Smadi & Al-Smadi (2024) utilized the System Generalized Method of Moments (Sys-GMM) technique to examine the interconnectedness of financial inclusion and FDI.

At this point, the conflicting findings of the studies of Jiang et al. (2024) and Uddin et al. (2024) may largely reflect differences in scope, regional context, and methodological choices. This raises concerns about the generalizability of such results, as institutional and regulatory settings strongly shape the impact of FinTech on FDI, particularly in studies confined to specific regions. Moreover, there remains a lack of insight into the global implications of this relationship, further underscoring the need for research that adopts a broader, cross-country perspective.

2.3.2 The Influence of FinTech development on Economic Performance

In general, existing studies reveal a complex and multifaceted influence of FinTech development on economic performance through direct and indirect impact. The existing research on this relationship varies across different conditions and specific interactions, as supported by the varied results from positive to mixed. Therefore, the need for further research in this manner remains crucial to the specific scope of study to further understand the impact of FinTech development.

In terms of the direct influence of FinTech development on economic performance, several studies have shown a positive and significant relationship between FinTech development and economic performance through its relevant indicators (Jafri et al., 2025; Mashamba et al., 2023; Salleh et al., 2025; Sayari et al., 2025). Specifically, the study of Jafri et al. (2025) employed the bibliometric and content analysis of 3884 FinTech manuscripts from the Scopus database, revealing strong and consistent evidence that FinTech serves as a key driver of economic sustainability. In contrast, the study of Mashamba et al. (2023) used the covariance-based structural equation modeling (SEM) and analyzed the 56 banks across 19 Sub-Saharan Africa (SSA) between 2010 and

2020 to examine the relationship. In the study, it was found that results of one-unit growth in FinTech activities will stimulate economic growth by approximately 17 units in SSA. Although Jafri's large-scale bibliometric analysis reveals consistent patterns, the reliance on bibliometric methods may impose certain limitations by reducing the depth and contextual richness of the findings compared to the study of Mashambe et al. (2023). Similarly, Salleh et al. (2025), who studied that environment in Malaysia, and Sayari et al. (2025), who compared the 30 developed and developing nations, reinforce this evidence by showing that FinTech acts as a catalyst for both economic and socioeconomic development. Their findings highlight FinTech's role in stimulating job creation, enhancing productivity, and supporting infrastructure development, particularly in contexts where traditional financial systems are less accessible.

However, some studies have also shown mixed and nuanced results in different conditions (Choudhary et al., 2025; Liu & Chu, 2024; Xu et al., 2024; Rahman et al., 2025). Evidence shows that Fintech positively enhance GDP up to the 50^{th} percentile; however, the effect is weaker and turns insignificant at the higher-level percentiles (Choudhary et al., 2025). Similarly, Liu and Chu (2024) highlighted that the impact of FinTech development on economic growth was particularly evident during the COVID-19 pandemic, with the benefits concentrated in countries with high internet penetration, based on a cross-country analysis of 193 nations from 2018 to 2021. Rahman et al. (2025) further supported the role of FinTech as a driver of economic recovery in BRICS nations. Nevertheless, Xu et al. (2024) cautioned that while FinTech can serve as a driver of growth, it may not be essential in all contexts, functioning more as a complementary rather than a foundational factor. Taken together, these results imply that rather than being always positive, the relationship between FinTech and economic growth depends on contextual circumstances, digital infrastructure, and developmental stage.

In contrast, Uddin et al. (2024), employing Data Envelopment Analysis (DEA) through Slack-Based Measure (SBM) and Epsilon-Based Measure (EBM) across 20 G20 countries from 2010 to 2022, found that the interaction between FinTech and FDI has a negative impact on environmental efficiency. They attribute this detrimental effect to FDI's emphasis on short-term gains, rapid expansion, and globally oriented supply chains that prioritize cost efficiency over sustainability. Similarly, Ochirova and Miriakov (2025), using data from 25 countries between 2008 and 2021, reported that FinTech mergers and acquisitions generate only a significant short-term abnormal return for acquiring companies, indicating that the market reaction to these events is temporary rather than sustained.

Collectively, although bibliometric studies provide consistent evidence of a positive relationship between FinTech and economic performance, findings across regions, countries, and time periods remain mixed. This suggests that FinTech's impact is conditional rather than uniform. Most existing studies are cross-country in nature (Choudhary et al., 2025; Jafri et al., 2025; Liu & Chu, 2024; Sayari et al., 2025), yet they employ diverse methodologies, which partly explains the variation in outcomes. These differences underscore the need for further research that explores contextual factors and adopts more integrative approaches to fully understand the dynamics of FinTech development and economic performance.

2.3.3 The Influence of FinTech development on the achievement of SDGs

With the growing significance of the Sustainable Development Goals (SDGs) in driving global sustainable development, the role of FinTech in supporting their achievement has also gained increasing attention. However, only certain SDGs have been explored in existing studies, leaving notable gaps in the literature. Moreover, empirical findings on the influence of FinTech development on SDG achievement remain mixed, often varying across different contexts. For clarity, the SDGs will be categorized into three dimensions, which are economic, society, and environmental, to provide a useful framework for understanding the recent findings of past studies in this section.

In the context of economic growth and innovation, existing studies have studied the relevant SDGs, which are SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 10 (Reduced Inequality) (Choudhary et al., 2025; Liu & Chu, 2024; Lee et al., 2024; Salleh et al., 2025). For SDG 8, which focuses on economic growth, the findings largely align with those discussed in Section 2.3.2 on the impact of FinTech development on economic performance. Similar to the discussion, the results reveal a similarly mixed and conditional set of findings, where FinTech contributes to GDP, job creation, and stimulates economic growth, but the impact decreases at higher percentiles. Furthermore, in relation to SDG 10, Salleh et al. (2025) reported significant evidence linking FinTech innovation to the reduction of inequality. Their study, based on the lived experiences of five Malaysian FinTech entrepreneurs using Interpretative Phenomenological Analysis (IPA), provides valuable qualitative insights into how FinTech enhances financial inclusion and digital service accessibility. However, the limited sample size and country-specific focus restrict the generalizability of the findings to a global context.

For SDG 9, the study of Choudhary et al. (2025) that utilized quantile regression analysis emphasized that FinTech positively enhances the internet, which is the proxy to SDG 9, up to the 50^{th} percentile, and a decreasing impact at higher percentiles. Overall, the study's conclusions continue to highlight how FinTech innovation drives infrastructure development and industrial growth by improving internet access, fostering digital inclusion, and bridging the digital divide. On the other hand, the study of Lee et al. (2024), which only focused on

China from 2003 to 2017, has revealed that FinTech promotes corporate innovation by reducing corporate financing constraints and financing costs. Notably, the effect was more pronounced for private, small, and young firms, particularly in regions with lower regulatory intensity, underscoring the influence of government policy. Despite differences in scope, where one offers a global perspective and the other a country-specific analysis, both studies consistently support a positive relationship between FinTech and the achievement of SDG 9.

Moving to the society dimension, Choudhary et al. (2025) examined several SDGs in relation to FinTech development, including SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-being), and SDG 4 (Quality Education), by using simultaneous equation modeling and quantile regression to examine Global Findex data from 86 nations (2011–2021). Although FinTech's effect on the overall SDG 2 score was insignificant, it and financial inclusion considerably decreased undernourishment across all quantiles for SDG 2, with larger effects in countries with high levels of undernourishment. Fintech was also crucial in reducing maternal mortality for SDG 3, demonstrating its significance as a facilitator of socioeconomic growth. While financial inclusion was insignificant, FinTech had a favorable impact at higher quantiles for SDG 4. Additionally, the reverse causality revealed that education is a major driver of both FinTech and inclusion.

Besides, in terms of environmental dimensions, SDG 13 (Climate Action) has also been widely studied in relation to FinTech development, with evidence pointing to both direct and conditional effects (Rahman et al., 2025; Sayari et al., 2025; Zhang et al.,2024). Specifically, Rahman et al. (2025) find that FinTech contributes significantly to renewable energy adoption and CO_2 emission reduction in BRICS countries, although its effectiveness depends on integration within broader economic and environmental frameworks. Similarly, Sayari and Abbassirabeh (2024) demonstrate that FinTech and digital transformation improve environmental performance through financial inclusion in 30 developed and developing nations; however, geopolitical risks can mitigate these advantages, underscoring the significance of a favorable political climate. In addition, Zhang et al. (2024) show that FinTech lowers CO_2 emissions in African economies, quantifying both short- and long-term reductions and highlighting the contribution of online financial activities to reducing carbon footprints. Additionally, the study of Croutzet and Dabbous (2021) investigated SDG 7 (Affordable and Clean Energy) across 21 OECD countries (2005–2018) using a fixed-effect panel regression model and found a significant positive relationship, where a one-unit increase in FinTech was associated with a 0.1901% rise in renewable energy consumption.

2.3.4 The Influence of FDI on Economic Performance

FDI has long been acknowledged as a critical determinant of economic growth, with numerous studies examining its role across different countries and contexts. However, empirical research on the matter often produced inconsistent, ambiguous, or conditional findings based on a number of variables, including the financial system, economic policies, absorptive capacity, and the degree of development of the host nation.

Firstly, even though the empirical findings are mixed, however, there is still prior research that has found positive and significant results for the relationship between FDI and economic performance. For instance, Alvarado et al. (2017), who utilized a panel data econometrics, found that FDI's impact in Latin America varies by income level. In detail, it is positive and significant in high-income countries like Chile and Uruguay, inconsistent in upper-middle-income nations, and negative in lower-middle-income countries. The conflicting results also highlighted how structural factors and absorptive capacity affect the efficiency of FDI. Similarly, An et al. (2025) also observed an inverted-U relationship between financial development and FDI's growth effect in emerging and developing Asia. These findings further highlighted that moderate levels of financial depth increase the benefits of FDI, while very high levels may lessen the benefits. However, the sampling period for Alvarado et al. (2017) and An et al. (2025) is 1980 to 2014 and 1996 to 2019, respectively, and covers different regions of the world. Therefore, it might cause a research gap with the recent trends of FDI globally.

Furthermore, other studies emphasize the importance of institutional and policy environments that will further affect the significance of FDI on economic performance. For example, Azman-Saini et al. (2010), who studied based on a panel of 85 countries over the 1995 to 2004 period, show that FDI by itself does not substantially increase growth. Instead, the benefits of FDI are shown in nations with high levels of economic freedom, highlighting the significance of supportive governance and regulatory frameworks. In addition, some studies caution that FDI can have neutral or even negative effects on the economic performance. In detail, Bermejo Carbonell and Werner (2018) report insignificant or slightly negative effects of FDI on Spanish GDP, potentially due to crowding out of domestic investment by utilizing the methodology of General-to-Specific (GETS) econometrics. Similarly, the study of Mahembe et al. (2016) further supports the mixed results, where the study found that in low-income Southern African Development Community (SADC) countries, FDI does not Granger-cause growth, and only in middle-income SADC nations does economic growth lead to FDI.

In addition, the study of Mahmoodi and Mahmoodi (2016) reveals bidirectional short- and long-term causal relationships between FDI, exports, and economic growth in developing countries in Europe and Asia, highlighting the complex feedback loops between FDI, trade, and GDP development. The study further emphasizes that the causal patterns vary across regions. Another important link is between FDI and financial inclusion. Al-Smadi and Al-Smadi (2024) find that increased financial inclusion in the Middle East and North African countries, through access to credit, ATMs, and deposit accounts, is positively correlated with FDI inflows and economic growth, suggesting a mutually reinforcing relationship between foreign investment and domestic financial capacity. Meanwhile, Xu et al. (2025) also emphasized that FDI is a necessary element for the expansion of tourism-dependent economies, which is related to the attractiveness of FDI inflow.

2.3.5 The Influence of FDI on the achievement of SDGs

As both FDI and the SDGs have gained increasing significance in recent years, this section will analyze the influence of FDI on the achievement of SDGs. Similar to the earlier sections, the SDGs will be categorized into three dimensions, which are economic, society, and environmental, to provide a useful framework for understanding the recent findings of past studies in this section.

In terms of SDG 8 (Decent Work and Economic Growth), the influence of FDI is highly discussed in Section 2.3.4, The Influence of FDI on Economic Performance. Overall, the results of studies show that there is a mixed and conditional relationship between FDI on SDG 8. Although FDI may boost economic expansion, its efficacy depends on regional, sectoral allocation, financial depth, institutional quality, and human capital. For example, Rodríguez-Chávez et al. (2024) also highlight regional disparities in Asia, showing that FDI-driven growth and sustainable development are stronger in areas with better infrastructure and institutional quality, while less developed regions face limitations that may exacerbate inequalities. Furthermore, for SDG 10 (Reduced Inequalities), evidence suggests that FDI can reduce income inequality by creating jobs in multinational corporations, which often require a skilled workforce, but can exacerbate inequality if it primarily employs high-skilled workers (Rodríguez-Chávez et al., 2024).

For SDG 4 (Quality Education), that relevant to the society dimensions, Alvarado et al. (2017) highlighted that higher investment in education strengthens FDI's contribution to economic growth, while low human capital may limit its benefits. In terms of SDG 7 (Affordable Clean Energy), the study of Croutzet & Dabbous (2021) that included 21 OECD countries (2005–2018) showed that FDI showed a negative and statistically significant effect on renewable energy consumption, suggesting that FDI reduces renewable energy use. In contrast, FDI also has a positive impact on energy efficiency through the reduction of renewable energy consumption (RENC) by driving technological and digital innovations. The results implied that FDI could lead to significant corporate spending, spurring digital and technological advances that could reduce overall energy consumption, not just that of renewable energy. Notably, existing studies still remain relatively underexplored regarding the role of FDI in achieving the SDGs, particularly regarding human capital development and inequality reduction (Rodríguez-Chávez et al., 2024). This underscores the need for further research focusing on societal impacts.

Furthermore, in relation to the environmental dimension, FDI can both positively and negatively affect environmental outcomes, revealing the nuanced relationship between economic growth and sustainability. Uddin et al. (2024) examined 20 G20 countries from 2010 to 2022 using Data Envelopment Analysis (DEA) and supplemented by Tobit regression and Generalized Method of Moments (GMM). Their results indicate that while FinTech positively enhances environmental efficiency and FDI generally contributes to improved eco-efficiency, the combination of FDI and FinTech investments can negatively impact environmental outcomes. This adverse effect is attributed to FDI's focus on short-term gains, rapid expansion, and globally oriented supply chains that prioritize cost efficiency over sustainability. In a related study, Zhang et al.

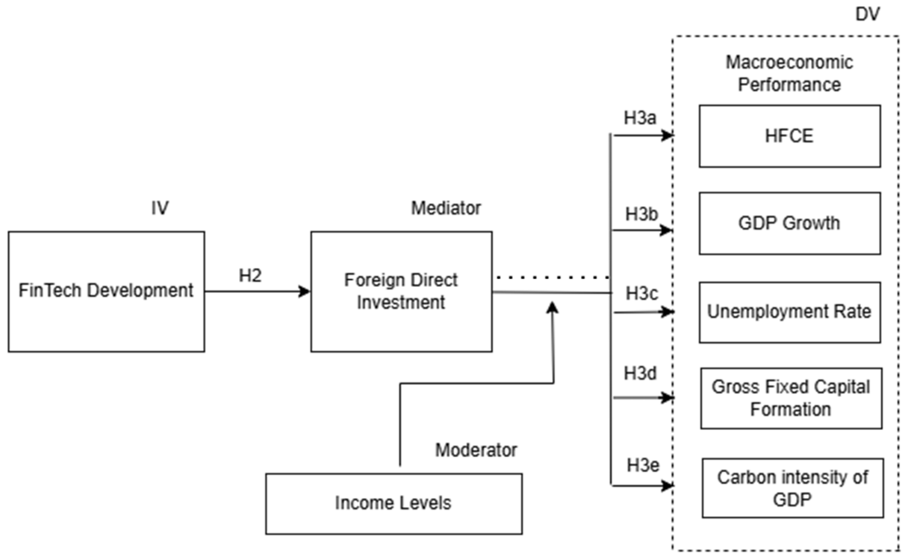
(2024) analyzed Chinese-invested African economies using panel ARDL models and DOLS for robustness. The study found that a 1% increase in Chinese outward FDI reduced CO_2 emissions by 0.5675%, while a 1% increase in FinTech development decreased CO_2 levels by 0.1864%. Additionally, higher energy consumption increased CO_2 emissions, whereas stronger economic performance helped lower emissions over the long run. Collectively, these studies suggest that both FDI and FinTech can support environmental sustainability, although the combined effects and regional contexts critically determine their overall impact.

In addition, FDI has the potential to support broader Sustainable Development Goals by bridging financing gaps, particularly in the least developed countries, if aligned with national and regional sustainable development strategies (Rodríguez-Chávez et al., 2024). Strategic policy measures, such as strengthening financial systems, enhancing institutional quality, and promoting the digital economy, can maximize FDI's contribution to economic, social, and environmental outcomes (Satyanand, 2021). However, FDI trends may concentrate investment in developed economies, potentially limiting gains in developing regions, highlighting the need for proactive policy interventions to guide sustainable FDI flows.

2.4 Theoretical/ Conceptual Framework for the Research

Building on the literature reviews, the conceptual framework that presents the overall picture and concept of this study has been developed as follows. As a highlight, in this study, two conceptual frameworks are developed to outline the relationship between FinTech development and FDI with economic performance and the achievement of the SDGs, respectively.

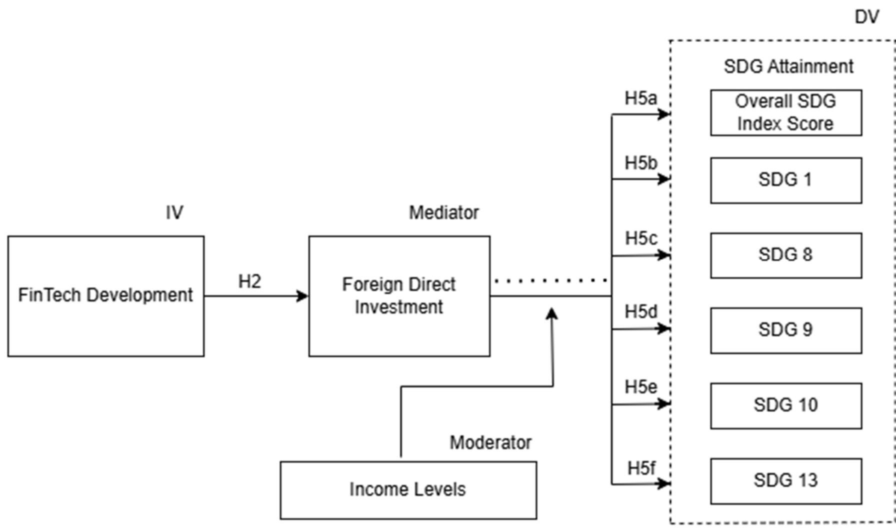
Figure 2.1: Conceptual Framework of Macroeconomic Performance



Sources: Developed for the research

As shown in Figure 2.1: Conceptual Framework of Macroeconomic Performance, it illustrates the direct and indirect relationships among FinTech development, FDI, and macroeconomic performance. In terms of economic performance, several variables are involved, including Households and Non-Profit Institutions Serving Households (NPISH) Final Consumption Expenditure (HFCE), GDP growth, unemployment rate, gross fixed capital formation, income inequality, and Carbon dioxide (CO_2) emissions. These variables are employed to capture the effects of FinTech development and FDI across the economic, social, and environmental dimensions. In addition, the moderator, which is the income level of the country, is applied to maintain consistency and enhance the ability to analyze the results further.

Figure 2.2: Conceptual Framework for the Achievement of SDGs



Sources: Developed for the research

Similarly, Figure 2.2: Conceptual Framework for the Achievement of SDGs illustrates the direct and indirect relationships among the variables. The notable difference is that the dependent variables are changed to the achievement of the SDGs. In this study, the focus is placed on the overall SDG Index score and on selected individual goals, specifically SDG 1, SDG 8, SDG 9, and SDG 13The achievement of the SDGs is treated as a long-term indicator compared with economic performance, which serves as a short-term measure and provides complementary insights. The same moderator, income level, is applied in this framework to examine how the relationships vary across different country classifications.

2.5 Hypotheses Development

Aligning with the general objectives of this study, which is examining the differences in FinTech development across different income level economies, the first hypothesis that provides a descriptive analysis has been formed as follows.

H1: There are significant differences in FinTech development among low-income, lower-middle-income, upper-middle-income, and high-income economies.

According to the International Investment Location Theory, it suggests that improved financial systems can enhance locational advantages and then further increase the FDI attractiveness. On the other hand, although Institutional Theory argues that the adoption of FinTech is often driven by global pressures and uncertainty rather than efficiency, it does not deny the rapid growth and expansion of FinTech development in the financial market. Therefore, it is expected that FinTech development positively influences FDI inflows. In addition, this relationship is also further supported by the study of Jiang et al (2024), where digital finance has a significant and positive effect on FDI for China. This relationship is further supported by the study of Jiang et al. (2024), which found that digital finance has a significant and positive effect on FDI in China. At the global level, Satyanand (2021) emphasized that the availability of e-payment systems, driven by FinTech, plays an important role in attracting FDI. Building on these theoretical and empirical insights, the following hypothesis is proposed:

H2: FinTech development positively impacts Foreign Direct Investment across low-income, lower-middle-income, upper-middle-income, and high-income economies.

Moreover, building on the FDI-Growth Spillover Theory, which suggests that there is a spillover effect of FDI that contributes to economic performance, especially through technology transfer, human capital formation, and infrastructure development, the influence of FDI on economic performance can be predicted as positive. Although the Absorptive Capacity Hypothesis argues that the benefits of FDI for economic growth depend on the ability of a country to absorb them, which is related to regulations, diversity of knowledge, and other factors, both theories still support the view that FDI has the potential to contribute to economic performance, with the only difference being that the results may vary across countries. Furthermore, this is also supported by the studies of Alvarado et al. (2017) and An et al. (2025), which focus on Latin America and emerging and developing Asia, respectively. While the findings show mixed results across income levels, most are positive and significant, supporting the view that the benefits of FDI depend on a country's absorptive capacity. Therefore, building on the theories and empirical studies mentioned above, the following hypothesis is formed.

H3a: FDI positively impacts Households and NPISH Final Consumption Expenditure (HFCE) across low-income, lower-middle-income, upper-middle-income, and high-income economies.

H3b: FDI positively impacts the GDP Growth across low-income, lower-middle-income, upper-middle-income, and high-income economies.

H3c: FDI negatively impacts the unemployment rate across low-income, lower-middle-income, upper-middle-income, and high-income economies.

H3d: FDI positively impacts the gross fixed capital formation across low-income, lower-middle-income, upper-middle-income, and high-income economies.

H3e: FDI negatively impacts the Carbon dioxide (CO2) emissions across low-income, lower-middle-income, upper-middle-income, and high-income economies.

According to the Endogenous Growth Theory (EGT), which emphasizes that human capital, skill levels, and technological progress are the key drivers of economic growth driven by market incentives, there is increasing interest and potential in the technology market. In this context, FinTech, which utilizes cutting-edge technologies, has demonstrated its ability to digitalize traditional financial systems. Therefore, building on this, FinTech development can be predicted to have a positive influence on the economic growth of countries. Existing studies also strongly support this argument, as most findings conclude a positive and significant relationship between FinTech development and economic performance (Jafri et al., 2025; Mashamba et al., 2023; Salleh et al., 2025; Sayari et al., 2025). These studies show consistent results, even though they focus on different regions such as Sub-Saharan Africa (SSA) and the top 30 developed and developing nations globally. Therefore, it is reasonable to confidently build the following hypothesis.

H4a: Fintech development positively impacts Households and NPISH Final Consumption Expenditure (HFCE) across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

H4b: Fintech development positively impacts GDP growth across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

H4c: Fintech development negatively impacts the unemployment rate across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

H4d: Fintech development positively impacts the gross fixed capital formation across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

H4e: Fintech development negatively impacts the Carbon dioxide (CO2) emissions across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

By applying the similar theory, which is FDI-Growth Spillover Theory, FDI is positioned as a driver of growth in economic, social, and environmental dimensions rather than merely a capital injection. This theory further suggests that FDI stimulates research and development, which fosters innovation and promotes long-term growth for a country. Such outcomes are highly aligned with the objectives of the SDGs. In addition, the study of Rodríguez-Chávez et al. (2024), Croutzet & Dabbous (2021) and Uddin et al. (2024) that studies on the effect in economic, social, and environmental dimensions respectively, further highlighted the relationship of FDI with respective indicator of economic performance. With the consistent results that obtained from the theory and existing studies, the hypotheses predicting a positive influence of FDI on the achievement of the selected SDGs are outlined as follows.

H5a: FDI positively impacts the Composite SDG Index Score across low-income, lower-middle-income, upper-middle-income, and high-income economies.

H5b: FDI positively impacts SDG 1 across low-income, lower-middle-income, upper-middle-income, and high-income economies.

H5c: FDI positively impacts SDG 8 across low-income, lower-middle-income, upper-middle-income, and high-income economies.

H5d: FDI positively impacts SDG 9 across low-income, lower-middle-income, upper-middle-income, and high-income economies.

H5e: FDI positively impacts SDG 10 across low-income, lower-middle-income, upper-middle-income, and high-income economies.

H5f: FDI positively impacts SDG 13 across low-income, lower-middle-income, upper-middle-income, and high-income economies.

According to the Innovation Diffusion Theory, the spread of innovations depends on their perceived advantages, communication channels, and social systems. In this context, FinTech innovations such as mobile banking and digital wallets reduce transaction costs, enhance financial inclusion, and accelerate technology adoption. As the diffusion of FinTech accelerates access and adoption, it supports progress in multiple SDGs, including decent work, reduced inequalities, and sustainable growth. Meanwhile, it also further supported by the study of Choudhary et al. (2025) that specifically study the effect of FinTech with composite and individual SDGs Index. Even though there are mixed results of direction of relationship for different income levels, however, the overall results showing a high potential of FinTech in positive influencing SDG achievement. Therefore, the hypothesis of FinTech development is expected to positively influence the achievement of selected SDGs, are outlined as follows:

H6a: Fintech development positively impacts the Composite SDG Index Score across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

H6b: Fintech development positively impacts SDG 1 across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

H6c: Fintech development positively impacts SDG 8 across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

H6d: Fintech development positively impacts SDG 9 across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

H6e: Fintech development positively impacts SDG 10 across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

H6f: Fintech development positively impacts SDG 13 across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI

2.6 Chapter Summary

Building on existing studies, this chapter synthesizes relevant theoretical and empirical findings to provide a solid foundation for examining the relationships between FinTech development, FDI, economic performance, and the achievement of SDGs. To better understand each variable and the interactions between them, established theories are used to offer different perspectives on these relationships. At the same time, a review of existing research highlights key trends and gaps, which collectively inform the development of the conceptual framework and hypotheses to be tested, ultimately aiming to generate meaningful insights.

Based on the research, the existing framework regarding the specific relationship of the variable is multifaceted. Therefore, different theories are employed for each key relationship. For instance, theories such as International Investment Location Theory, Endogenous Growth Theory, and Innovation Diffusion Theory provide the basis for predicting positive outcomes, while alternative frameworks like Institutional Theory, the Too Much Finance Hypothesis, and Complex Systems Theory highlight potential risks and conditional effects for the relationship between FinTech, FDI, economic performance, and SDGs.

Drawing on the core concepts of the theory, this chapter also reviews previous studies on the variables and their interrelationships to uncover trends, identify gaps in the literature. Notably, the review of past empirical studies reveals that the relationships between these variables are complex, often producing mixed and conditional findings. While some studies show that FinTech positively influences FDI and economic growth, others find the effects to be negative or dependent on factors like a country's income level, digital infrastructure, or institutional quality. Likewise, FinTech's impact on SDGs, such as decent work (SDG 8), innovation (SDG 9), reduced inequality (SDG 10), and climate action (SDG 13), the results are generally positive but vary in significance across different contexts.

This comprehensive review culminates in the development of two conceptual frameworks: one for short-term macroeconomic performance and another for long-term SDG achievement. Both models position FinTech as a driver that directly and indirectly, through FDI in influencing development outcomes, with a country's income level acting as a moderating factor. Based on the review of theories and past studies, the study formulates a series of hypotheses. These hypotheses predict that FinTech development will differ across income levels, positively impact FDI, and, through FDI's mediating role, will enhance both macroeconomic performance and the attainment of various SDGs.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter presents the methodological framework designed to investigate the relationships between FinTech development, Foreign Direct Investment (FDI), economic growth, and the attainment of Sustainable Development Goals (SDGs) across countries with varying income levels. To achieve these objectives, the chapter outlines the complete research process. Specifically, it introduces the research design, including the type of research, the type of data involved, and other relevant elements. Following this, the chapter details the sampling design, describing the sample characteristics, data sources, sampling period, and sampling method applied. The procedures for data collection and preparation are also explained, with particular emphasis on the construction of a balanced panel dataset to ensure analytical robustness. Importantly, this chapter also presents the econometric models developed to test each hypothesis, together with the statistical techniques and diagnostic tests employed to validate the models and rigorously evaluate the study's hypotheses.

3.1 Research Design

Aligning with the objectives of this research, quantitative research has been adopted as the predominant approach, as it allows for measuring the relationships between variables, testing hypotheses, and identifying generalizable patterns in the results. In addition, this study focuses on analyzing numerical and macroeconomic data from various economies grouped by income level. Therefore, the quantitative method is more suitable for handling large datasets and identifying statistical correlations. By contrast, qualitative methods, which are more exploratory and context-specific through approaches such as interviews, case studies, and observations, face limitations in measuring macro-level causal relationships and present difficulties in making cross-income-level comparisons. Since this study relies heavily on statistical and econometric techniques for analysis, it further highlights the need for a quantitative method to establish causal links between FinTech, FDI, economic growth, and SDG attainment across different income levels.

In addition, this study will also rely on secondary data that primarily comes from reliable sources such as the World Bank, IMF, and UNCTAD. One of the reasons for this choice is the need to deal with large-scale, national-level variables. Furthermore, the secondary data collected from the sources mentioned above can ensure consistency and reliability, providing meaningful insights for this study. Meanwhile, this study adopts secondary rather than primary data because primary data collection methods, such as surveys and interviews, are impractical at the scale required for global coverage and are unable to capture historical trends. Therefore, in consideration of practicality and consistency, secondary data is the more suitable method for this study. To be more specific, a panel dataset will be compiled to capture a clearer picture of the results, both in terms of time period and cross-sectional dimensions. Panel data is particularly valuable as it controls for country-specific differences and allows the analysis of changes over time, making the findings more robust and reliable.

As mentioned earlier, the scope of this study is to analyze the relationships among the various variables. Therefore, to be effective, both descriptive and causal analyses are designed to generate a comprehensive and robust investigation of the data. The descriptive analysis is intended to summarize the key variables and identify initial patterns and trends at the early stage. Furthermore, causal analysis will be applied to test the hypotheses outlined, determining the direction and strength of the relationships among the variables. The causal analysis is important as it establishes cause-and-effect relationships, quantifies the magnitude of effects, and highlights how they differ across various income-level economies in this study.

3.2 Sampling Design

In this research, the sampling period spans from 2017 to 2023, providing a recent and policy-relevant timeframe for analysis. The starting point of 2017 is chosen based on the official implementation of the 17 SDGs under the 2030 Agenda for Sustainable Development, which began in January 2016 (United Nations, 2016). However, due to incomplete data coverage in 2016, the following year, 2017, is selected as the starting point to ensure greater consistency and comparability across countries. The data is collected up to 2023 to ensure the use of the most recent and reliable information, as a substantial portion of the 2024 data remains unavailable. The issue of data unavailability is most severe for the proxies of FinTech development, namely, Individuals using the Internet (% of population) and Mobile cellular subscriptions (per 100 people). Missing data for these key independent variables may limit the scope of this study. Additionally, the data on Carbon dioxide (CO_2) emissions has not yet been fully updated in the World Bank database, while other variables still present incomplete datasets. Therefore, 2023 is chosen as the cut-off year for analysis, as it provides the most complete and updated dataset available for the variables under this study.

For the sampling framework, judgmental or purposive sampling is used, where only countries with available data that meet the required criteria are included in this study. The choice of purposive sampling, rather than random or stratified sampling that is typically used in selection models, is due to the limitations of secondary data availability. In addition, given that the scope of this study is global, complete and consistent data are highly required to generate meaningful insights. Therefore, purposive sampling is appropriate, as it ensures that the analysis is based on reliable and comparable data across countries, while also addressing the challenges of missing or incomplete information. The final number of countries depends on data availability across variables and is 54 in total.

Furthermore, all selected countries will be classified into four income-level groups based on the latest World Bank country classification methods. In detail, the countries will be categorized into four national income levels: low-income (< $1,145), lower-middle-income ($1,146 - $ 4,515), upper-middle-income ($4,516 - $14,005), and high-income (>$14,005), according to their Gross National Income (GNI) per capita (World Bank, 2024). The classification of countries in the sampling design, which follows a globally recognized standard, enables meaningful comparisons across different stages of development. This approach provides a deeper understanding of how the effects of the studied variables may vary across income levels, ensuring both analytical rigor and policy relevance. The details of the selected countries are presented in Table 3.1: Selected Countries.

Table 3.1: Selected Countries

Low-Income Economies (1)	**Lower-Middle-Income Economies (8)**	**Upper-Middle-Income Economies (18)**	**High-Income Economies (28)**
Rwanda	Bangladesh	Albania	Austria
	Ghana	Argentina	Belgium
	Honduras	Armenia	Bulgaria
	Lesotho	Botswana	Chile
	Timor-Leste	Brazil	Costa Rica
	Tunisia	Colombia	Croatia
	Vietnam	Dominican Republic	Cyprus
	Zimbabwe	Ecuador	Czechia
		Guatemala	Denmark
		Indonesia	Estonia

		Malaysia	Finland
		Mauritius	France
		Mexico	Greece
		Moldova	Hungary
		Mongolia	Korea, Rep.
		North Macedonia	Latvia
		Thailand	Lithuania
		Türkiye	Luxembourg
			Netherlands
			Panama
			Poland
			Portugal
			Russian Federation
			Slovak Republic
			Slovenia
			Spain
			Sweden
			Switzerland

Source: Author's own compilation.

3.3 Scale and Measurement of Variables

The independent variable in this research is FinTech development. Since there is no universally standardized measurement for FinTech, this study adopts proxy indicators to capture its dimensions, focusing on digital connectivity, digital financial usage, and mobile access. Specifically, FinTech development is measured using four proxies, which are the number of FinTech startups annually, the percentage of individuals using the Internet (digital connectivity), the number of mobile and internet banking transactions (digital financial usage), and mobile cellular subscriptions (mobile access). The selection of these measurements is based on the foundation of FinTech, which is enabled by technology and enhances the financial industry by making services faster, more efficient, and more accessible. Therefore, these three indicators are considered the most suitable, as they capture both the technological infrastructure that enables FinTech growth and the actual usage of digital financial services by the population. On the contrary, the alternative measures of FinTech development, such as the number of start-ups, registered capital, or composite indexes (Financial Development Index, IFZ rankings), are excluded as they lack directness and standardization across countries. In addition, their inconsistent availability across countries and years would substantially reduce the sample size of this study.

Furthermore, there are two main dependent variables to be analyzed in the study, which represent short-term and long-term effects for the testing relationship, respectively. For the short-term effect, it is represented by the macroeconomic performance in analyzing the impact of FinTech development and FDI. In detail, the measurement of economic performance includes Households and NPISH Final Consumption Expenditure, GDP Growth, Unemployment, total (% of total labor force), Gross fixed capital formation (% of GDP), and Carbon dioxide (CO2) emissions. The selection of these measurements is largely due to the relevance and consistent usage in the existing studies, which indicates their value in capturing essential aspects of an economy, especially indicators like GDP, Unemployment Rate, and consumer expenditure. In addition, these indicators provide a comprehensive view of overall economic performance from different perspectives, such as output, demand, and capital accumulation, while also enabling evaluation across multiple dimensions, which are social, economic, and environmental.

On the other hand, there is a composite SDG index score, and individual SDGs, which are SDG 1: No Poverty, SDG 8: Decent Work and Economic Growth, SDG 9: Industry, Innovation and Infrastructure, SDG 10: Reduced Inequalities, and SDG 13: Climate Action, are included as another dependent variable in this study. Building on the economic performance indicators, all of the individual SDGs that are rooted in the direct and significant connections with FinTech and FDI are selected to reflect long-term effects for the financial and technological advancements. Different from existing studies, the composite SDG Index Score is also included in this study, to provide an overall assessment of a country's progress towards the UN 2030Agenda. This dual approach ensures both depth and breadth by examining the specific SDGs most relevant to FinTech and FDI separately, as well as the composite SDG index.

In addition, this study also includes a mediator variable, which is Foreign Direct Investment (FDI), positioned between the independent and dependent variables. FDI is measured by foreign direct investment, net inflows (% of GDP), which is a widely used and standard indicator in cross-country analyses. In this study, FDI plays a crucial role in testing both the direct and indirect relationships between the independent and dependent variables, thereby providing deeper insights into the transmission mechanisms that link FinTech development, economic growth, and SDG attainment.

Specifically, the FinTech measure BankTrans is transformed using a logarithmic function due to the high variation detected in the sample. For FDI and CO_2, which also exhibit large standard deviations, a logarithmic transformation is not applied, as the original values are used to better capture more accurate and real-life outcomes. At the same time, the SDG indicators are measured using the same approach without logarithmic transformation. This consistent treatment further ensures the reliability and accuracy of the results.

Finally, Table 3.2: List of Measurement of Variables provides a detailed overview of each variable, their measurement indicators, supporting articles, and the data sources adopted from existing studies.

Table 3.2: List of Measurement of Variables

Variable	**Measurement of Variables**	**Supporting Articles**	**Sources Referenced in Articles**	**Final Data Sources for this Research**
Fintech Development	Number of FinTech Startup Annually	(Xu et al., 2024; Uddin et al., 2024)	CrunchBase	CrunchBase
	Individuals using the Internet (% of population)	(Sayari et al., 2025; Xu et al., 2024)	World Bank: World Development Indicators (WDI)	World Bank: World Development Indicators (WDI)
	Number of mobile and internet banking transactions (during the reference year)	(Choudhary et al., 2025)	International Monetary Fund’s Financial Access Survey	International Monetary Fund's Financial Access Survey (FAS)

	Mobile cellular subscriptions (per 100 people)	(Choudhary et al., 2025; Mashamba et al., 2023)	International Telecommunication Union (ITU)	World Bank: World Development Indicators (WDI)
Foreign Direct Investment	Foreign direct investment, net inflows (% of GDP)	(An et al, 2025; Azman-Saini, Baharumshah, & Law, 2010; Xu et al., 2024; Al-Smadi & Al-Smadi, 2024)	World Bank: World Development Indicators (WDI)	World Bank: World Development Indicators (WDI)
Macroeconomic Performance	Households and NPISH Final Consumption Expenditure (HFCE)	(Luo, Sun, & Zhou, 2022)	China Family Panel Studies (CFPS)	World Bank: World Development Indicators (WDI)
	GDP Growth	(Alvarado et al., 2017; Mahmoodi & Mahmoodi, 2016)	World Bank: World Development Indicators (WDI)	World Bank: World Development Indicators (WDI)

	Unemployment, total (% of total labor force)	(Liu & Chu, 2024; Zhang et al., 2024)	World Bank: World Development Indicators (WDI)	World Bank: World Development Indicators (WDI)
	Gross fixed capital formation (% of GDP)	(Alvarado et al., 2017; Choudhary et al., 2025)	World Bank: World Development Indicators (WDI)	World Bank: World Development Indicators (WDI)
	Carbon dioxide (CO2) emissions (total) excluding LULUCF (Mt CO2e)	(Uddin et al., 2024)	World Bank: World Development Indicators (WDI)	World Bank: World Development Indicators (WDI)
Sustainable Development Goals	Composite SDGs Index Score	(Morales-Casetti et al., 2025)	Sustainable Development Report 2023	Sustainable Development Report
	SDG 1: No Poverty	(Morales-Casetti et al., 2025)	Sustainable Development Report 2023	Sustainable Development Report
	SDG 8: Decent Work and Economic Growth	Choudhary et al., 2025; Salleh et al., 2025	World Bank: World Development Indicators (WDI)	Sustainable Development Report

	SDG 9: Industry, Innovation and Infrastructure	Choudhary et al., 2025; Salleh et al., 2025	International Telecommunication Union (ITU).	Sustainable Development Report
	SDG 10: Reduced Inequalities	(Demir et al., 2022)	Standardised World Income Inequality Database (SWIID)	Sustainable Development Report
	SDG 13: Climate Action	(Rahman et al., 2025; Uddin et al., 2024)	Sustainable Development Goal Index (SDGI) & World Bank: World Development Indicators (WDI)	Sustainable Development Report

Sources: Developed for the research

3.4 Data Collection & Preparation Procedures

The data for the variables will be sourced primarily from the World Bank Database, specifically the World Development Indicators (WDI). The data obtained from the WDI includes the variables of FinTech development, FDI, and economic performance. The WDI provides a compilation of cross-country comparable data derived from officially recognized sources, including national official statistical organizations, national accounts data files, the Organization for Economic Co-operation and Development

(OECD), the World Bank itself, etc. These sources ensure the consistency, reliability, and international comparability of the data used in this study.

In addition, the International Monetary Fund's Financial Access Survey (FAS) database is employed to obtain one of the proxy indicators for FinTech development, specifically the number of mobile and internet banking transactions. The IMF FAS is a reliable platform that provides annual, internationally comparable data on access to and usage of financial services. For SDG-related data, this study utilizes the annual Sustainable Development Report that was developed by Sustainable Development Solution Networks (SDSN). The SDG Index within the report is compiled from multiple internationally recognized datasets and provides a comprehensive evaluation of each country's progress toward the 17 Sustainable Development Goals. The detailed measurements of each of the variables are provided in Table 3.2: List of Measurements of Variables.

Following the collection of raw data from the sources mentioned, the dataset was organized into a balanced panel, which means every cross-sectional unit has observations for all time periods in the sample. A balanced panel is employed in this research to ensure the robustness and reliability of the analytical results. A balanced panel can also simplify the process of statistical testing due to some tests are designed with the assumption of a balanced dataset, for example, fixed effects models and the Hausman test. Most importantly, using a balanced panel helps mitigate selection bias, as missing observations are often non-random.

In detail, for the preparation procedures of the complete dataset, several refinement and filtering processes are applied to the dataset to ensure comparability and consistency. The same filtering and preprocessing steps to create a balanced panel are carried out across all raw data derived from the different sources mentioned earlier. First, all data are restricted to the sampling period of 2017–2023, reflecting the most recent and updated information for all indicators. After the timeframe selection, imbalances in the dataset emerge due to missing values across different indicators. To address this, purposive sampling is applied to ensure completeness, whereby countries with substantial missing data are excluded. At this stage, the cross-sectional data, countries with complete datasets covering FinTech development, FDI, economic performance, and SDGs, are retained. Finally, the retained countries are classified into different income-level groups, which are low-income, lower-middle-income, upper-middle-income, and high-income economies according to the World Bank's income classification as shown in Table 3.1 above.

3.5 Statistical Techniques and Tests

The analysis will begin with descriptive statistics to summarize all variables across countries, including FinTech development, FDI, and SDGs, among others. Specifically, the descriptive analysis will involve calculating measures such as the mean, median, standard deviation, minimum, and maximum. Additionally, for the moderator variable income level groups, a frequency distribution will be conducted to provide a clearer understanding of the dataset. These analyses will also help identify any anomalies or outliers in the data, which is essential prior to conducting any further analysis to ensure the accuracy and reliability of the results.

To test H1, which is a comparative hypothesis to test whether FinTech development varies across income levels, a one-way ANOVA will be employed. ANOVA is a suitable statistical test because it allows for the comparison of mean values across two or more independent groups. However, there are certain assumptions required for ANOVA testing, particularly normality and homogeneity of variances. Therefore, if these assumptions are violated, the non-parametric test, which is the Kruskal-Wallis test, will be further used for analysis. This approach ensures the robustness and validity of the results.

Before conducting further analyses, the dataset will be prepared as a balanced panel (normal panel) to ensure robustness and consistency across countries and years, simplify interpretation, and reduce potential bias from missing observations (Choudhary et al., 2025; Croutzet & Dabbous, 2021; Zhou et al., 2024). On top of that, panel regression analysis will be conducted, particularly for H2 to H6, with the statistical model outlined as follows:

H2: $FDI_{it} = \beta_0 + \beta_1 Startup_{it} + \beta_2 Internet_{it} + \beta_3 BankTrans_{it} + \beta_4 Mobile_{it} + \varepsilon_{it}$

H3a: $HFCE_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H3b: $GDP_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H3c: $Unemployment_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H3d: $GFCF_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H3e: $Gini_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H3f: $CO2_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H4a:

(i) $HFCE_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $HFCE_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $HFCE_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H4b:

(i) $GDP_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $GDP_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $GDP_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H4c:

(i) $Unemployment_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $Unemployment = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $Unemployment_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H4d:

(i) $GFCF_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $GFCF = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $GFCF_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H4e:

(i) $CO2_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $CO2 = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $CO2_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H5a: $SDG\ Index_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H5b: $SDG1_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H5c: $SDG8_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H5d: $SDG9_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H5e: $SDG10_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H5f: $SDG13_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H6a:

(i) $SDG\ Index_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $SDG\ Index_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $SDG\ Index_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H6b:

(i) $SDG1_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $SDG1_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $SDG1_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H6c:

(i) $SDG8_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $SDG8_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $SDG8_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H6d:

(i) $SDG9_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $SDG9_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $SDG9_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H6e:

(i) $SDG10_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $SDG10_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $SDG10_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

H6f:

(i) $SDG13_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(ii) $SDG13_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

(iii) $SDG13_{it} = \beta_0 + \beta_1 FinTech\ Development_{it} + \beta_2 Income\ Level_{it} + \beta_3 INFinTech\ Development_{it} + \beta_4 FDI_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$

Where:

- FDI_{it}= Foreign Direct Investment for country i at time t
- $Startup_{it}$= Number of FinTech Startups annually for country i at time t
- $Internet_{it}$= Individuals using the Internet (% of population) for country i at time t

- $BankTrans_{it}$= Log of the number of mobile and internet banking transactions (during the reference year) for country i at time t
- $Mobile_{it}$= Mobile cellular subscriptions (per 100 people) for country i at time t
- $HFCE_{it}$ = Households and NPISH Final Consumption Expenditure (% of GDP) for country i at time t.
- GDP_{it} = GDP Growth for country i at time t.
- $Unemployement_{it}$ = Unemployment, total (% of total labor force) for country i at time t.
- $GFCF_{it}$ = Gross fixed capital formation (% of GDP) for country i at time t.
- $CO2_{it}$ = Carbon dioxide (CO2) emissions (total) excluding LULUCF (Mt CO2e) for country i at time t.
- $SDG\ Index_{it}$ = Composite SDG Index Score for country i at time t.
- $SDG1_{it}$ = Individual SDG 1 Index Score for country i at time t.
- $SDG8_{it}$ = Individual SDG 8 Index Score for country i at time t.
- $SDG9_{it}$ = Individual SDG 9 Index Score for country i at time t.
- $SDG10_{it}$ = Individual SDG 10 Index Score for country i at time t.
- $SDG13_{it}$ = Individual SDG 13 Index Score for country i at time t.
- $Income\ Level_{it}$ = Income level for country i at time t.
- $INFDI_{it}$ = Foreign Direct Investment multiplied by the income level for country i at time t
- α_i= unobserved country-specific effects (time-invariant)
- γ_t= time-specific effects (shocks common across countries).
- ε_{it}= error term capturing unobserved factors

$FinTech\ Development_{it}$ including:

- $Startup_{it}$= Number of FinTech Startups annually for country i at time t
- $Internet_{it}$= Individuals using the Internet (% of population) for country i at time t
- $BankTrans_{it}$= Log of the number of mobile and internet banking transactions (during the reference year) for country i at time t
- $Mobile_{it}$= Mobile cellular subscriptions (per 100 people) for country i at time t

$INFinTech\ Development_{it}$ including:

- $\text{INStartup}_{\text{it}}$= Number of FinTech Startups annually multiplied by the income level for country i at time t
- IN $\text{Internet}_{\text{it}}$ = Individuals using the Internet (% of population) annually multiplied by the income level for country i at time t
- $\text{INBankTrans}_{\text{it}}$= Log of the number of mobile and internet banking transactions (during the reference year) annually multiplied by the income level for country i at time t
- $\text{INMobile}_{\text{it}}$= Mobile cellular subscriptions (per 100 people) multiplied by the income level for country i at time t

As outlined in the econometric model section, panel data regression will be employed for testing hypotheses H2 to H6, given the data structure that combines both cross-sectional and time-series dimensions. Specifically, for H2, panel regression will be conducted to examine the direct effect of FinTech development on FDI. For H3 and H4, the focus is on assessing the effects of FDI and FinTech on economic performance, both in terms of direct impacts and indirect effects through FDI. Similarly, H5 and H6 extend the analysis to sustainable development outcomes, where panel regression is applied to test the impact of FinTech and FDI on the composite SDG index as well as on the individual SDGs indicators. For all hypotheses, the null hypothesis assumes no significant effect ($\beta_1 = 0$), while the alternative assumes a significant relationship in the expected direction. The decision rule is based on the p-value of the estimated coefficient: results with $p < 0.01$ are interpreted as strong evidence, results with $0.01 \leqslant p < 0.05$ are considered significant evidence, and results with $0.05 \leqslant p < 0.10$ are regarded as marginal evidence. Coefficients with $p \geqslant 0.10$ are treated as statistically insignificant.

At the same time, model selection between pooled OLS (POLS), fixed effects (FEM), and random effects (REM) will be based on the Breusch–Pagan LM test, the Redundant Fixed Effects test, and the Hausman test. The Breusch–Pagan LM test is applied first to test for random effects, which is about whether panel variation is present. In detail, the null hypothesis assumes that there is no panel-level variance ($H_0 = no\ random\ effects$). For the decision rule of this test, if p $\geqslant 0.10$, the null hypothesis cannot be rejected, which means POLS is sufficient. In contrast, if p<0.05, FEM or REM is considered for the model selection. The Redundant Fixed Effects test is then used to examine whether entity-specific effects are jointly significant, where the null hypothesis will be set that all fixed effects are equal to 0 ($H_0: all\ \alpha_i = 0$). Similarly, if the p<0.05, reject the null hypothesis, and this result indicates that unobserved heterogeneity across entities is significant, and further supports the use of FE, over POLS, and vice versa. Furthermore, the Hausman Test is applied to decide the use of FEM or REM. In detail, the null hypothesis assumes that REM is inconsistent ($H_0: Cov(\alpha_i, X_{it}) = 0$) and vice versa for the alternative hypothesis. If the p<0.05, reject the null hypothesis, and this result indicates FEM is consistent and preferable in application. Besides, due to restrictions in Stata, for models that violate the standard assumptions of the Hausman test, the Sargan–Hansen test is applied as an alternative to further determine the preferable use of REM or FEM.

Notably, before conducting regression analysis, diagnostic tests will be carried out to ensure the validity and reliability of the models, including checks for stationarity of datasets, multicollinearity, heteroskedasticity, autocorrelation, and normality of residuals. These tests help to detect potential model misspecifications at an early stage, allowing appropriate remedies to be applied and thereby enhancing the robustness and reliability of the estimated results.

The first diagnostic test is the unit root test, which is conducted to examine the stationarity of the dataset using the Augmented Dickey–Fuller (ADF) test. In this test, the null hypothesis assumes the presence of a unit root, indicating that the dataset is non-stationary, while the alternative hypothesis assumes stationarity. If the p-value is less than 0.05, the null hypothesis can be rejected, suggesting that the data satisfy the stationarity assumption and are free from stationarity issues. In contrast, if the p-value is greater than 0.05, the dataset is considered to have a stationarity issue. To address this issue, remedies such as differencing are applied to ensure the validity and reliability of the regression results.

The next diagnostic test is the check for multicollinearity using variance inflation factors (VIF), which is also one of the key assumptions for models such as POLS. In the multicollinearity testing, the null hypothesis assumes that no multicollinearity exists, and vice versa for the alternative hypothesis. If the results of the VIF values are below the threshold of 5, it indicates that multicollinearity is not a concern in the model. If the VIF values are between 5 and 10, multicollinearity may still be a concern, although it is generally not considered a serious issue. In contrast, if the VIF value is above 10, it means a potential issue in terms of multicollinearity. In this situation, some remedies can be applied, including dropping highly correlated variables, applying a transformation, or using dimension-reduction techniques such as principal component analysis. Additionally, if multicollinearity leads to unstable or nonlinear effects, models such as Panel Smooth Transition Regression (PSTR) or Panel Threshold Regression (PTR) may be applied to capture regime-specific dynamics more reliably.

In addition, assessments of heteroskedasticity using the Breusch-Pagan-Godfrey and White test will be conducted to verify consistent error variance across observations. In detail, the null hypothesis of both tests assumes homoskedasticity, which means constant variance of the residuals. If the $p < 0.05$, the null hypothesis will be rejected, indicating there is presence of heteroscedasticity, which volatile the assumptions of the model. To address potential violations, robust standard errors or generalized least squares (GLS) can be employed to correct for heteroskedasticity and thereby improve the reliability of the estimated results. Meanwhile, if the heteroskedasticity is linked to endogeneity, GMM estimators can further be applied to provide consistent results.

Autocorrelation testing will also be carried out to detect potential correlations between residuals over time through the Wooldridge Test. In this test, the null hypothesis assumes no autocorrelation and vice versa for the alternative hypothesis. The rejection of the null hypothesis will occur when $p < 0.05$, indicating autocorrelation exists. In the situation of existence of autocorrelation, the remedies include incorporating lagged dependent variables, respecifying the model, or applying feasible GLS estimators can be applied to address the potential issues. Similarly, if autocorrelation interacts with nonlinear adjustments, PTR or PSTR can be used to model threshold-driven persistence.

Another diagnostic test is the normality test, which will be conducted to verify whether the residuals satisfy the distributional assumptions of the regression model. The example of a test to check normality is the Jarque-Bera test. Specifically, the null hypothesis assumes normality. However, by applying the Central Limit Theorem (CLT), the dataset used in this research—which includes 55 countries over 7 years—is considered a large sample, as it exceeds the minimum requirement of 30 observations to be classified as a large sample. Therefore, given that the dataset is sufficiently large, violations of the normality assumption are not considered a serious issue, as the sampling distribution of the estimators is expected to be approximately normal. This ensures that the regression estimates remain reliable and valid despite potential deviations from normality in the underlying data, therefore, a normality test is not further required as part of the diagnostic tests.

3.6 Chapter Summary

In conclusion, this chapter has outlined a comprehensive quantitative research methodology to investigate the intricate relationships between FinTech development, FDI, macroeconomic performance, and the attainment of SDGs. This study relies exclusively on secondary data sourced from reputable international organizations such as the World Bank, the IMF, and the UNCTAD. Specifically, the sampling design involves a purposive selection of 54 countries based on data availability for the study period, which spans from 2017 to 2023. The selected countries are categorized into four income groups—low, lower-middle, upper-middle, and high-income—based on the World Bank's classification system, allowing for a nuanced, comparative analysis across different stages of economic development.

Meanwhile, the key variables that are employed in this study are measured by specific proxies. For instance, FinTech Development is measured by internet usage, mobile/internet banking transactions, and mobile subscriptions, while FDI is measured by net inflows as a percentage of GDP. Additionally, this study covers both macroeconomic performance and SDG attainment as the dependent variables to capture the short-term and long-term effects. Notably, all of the collected data is then compiled into a balanced panel dataset, which enhances the robustness of the findings by controlling for country-specific differences and tracking changes over time. This process involves filtering out countries with incomplete data to mitigate selection bias and ensure the reliability of the statistical analysis.

Furthermore, to generate a comprehensive analysis, statistical techniques and tests are required to test the hypothesis. Specifically, the analysis will employ descriptive statistics, ANOVA, or the Kruskal-Wallis test to compare FinTech development across income levels. The core of the analysis will involve panel regression models to test the study's main hypotheses concerning the direct and indirect effects of FinTech and FDI on economic and sustainable development outcomes. The selection between pooled OLS, FEM, and REM will be guided by standard econometric tests like the Breusch-Pagan LM and Hausman tests. To ensure the validity of the results, a series of diagnostic tests will also be conducted, including checks for multicollinearity, heteroskedasticity, autocorrelation, and the normality of residuals, with clear remedies outlined for any potential issues identified.

CHAPTER 4: RESULTS & DISCUSSION

4.0 Introduction

This chapter presents detailed data analysis based on the outlined research questions. As a prescreening step, a detailed descriptive analysis across different income levels has been conducted to better understand the raw data of the key variables included in this study. Model selection and a series of diagnostic tests, including unit root tests, multicollinearity, heteroskedasticity, and autocorrelation, have been carried out to ensure the reliability and accuracy of the results. Specifically, appropriate remedies, which are the mean centering approach and cluster robust standard error have been applied to the models where issues were identified. Furthermore, this chapter presents the regression analysis with a detailed discussion of the results, in order to further analyse the relationships between FinTech development, FDI, macroeconomic performance, and the achievement of the SDGs.

4.1 Descriptive Analysis

The descriptive analysis will provide a basic understanding of the data collected for each variable, which is essential for further hypothesis testing. This section presents both overall and income-level group descriptive analyses to comprehensively examine the data and highlight differences across countries by income classifications.

4.1.1 Overall Variables

Table 4.1: Overall Descriptive Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum	Kurtosis	Skewness
Startup	11.5533	16.8287	0	112	13.6480	2.8640
Internet	74.3992	19.3042	17.2000	99.3000	3.4700	-1.1159
BankTrans	9.8634	3.1493	-6.0504	13.4961	14.1201	-3.0395
Mobile	121.9977	22.4764	68.1001	181.2220	3.0921	0.0610
FDI	3.2803	42.8923	-444.7069	431.7885	73.1584	0.2333
HFCE	2.7794	4.9794	-17.0821	20.8394	5.1465	-0.4019
GDP	2.7341	5.0931	-20.5416	31.9619	8.5248	-0.3437
Unemployment	7.4869	4.7757	0.7160	23.6150	3.8926	1.1698
GFCF	22.3450	5.0495	9.6504	39.3363	3.1982	0.1751
CO2	142.9104	289.6854	0.6499	2069.5020	26.4351	4.4187
SDGIndex	73.7886	7.6565	54.7869	87.0992	2.5975	-0.5452
SDG1	88.6136	19.9484	18.4250	99.9800	6.9494	-2.2086
SDG8	73.8423	6.7558	46.8403	84.8729	4.4978	-1.0447
SDG9	60.7915	22.3312	20.8988	99.6504	1.9611	0.1924
SDG10	67.0816	28.5059	12.8170	100.0000	1.8391	-0.5726
SDG13	83.2748	11.6842	40.5267	98.8610	3.8916	-0.9901

Table 4.1 above summarizes the main variables related to FinTech development, FDI, macroeconomic performance, and sustainable development with a detailed analysis based on the central tendencies, variability, and distributional characteristics. Each variable is discussed in detail below.

For FinTech development, the first variable, Internet, shows a high mean value of 74.3992, indicating that about 74% of the population across countries uses the Internet. The standard deviation of 19.3% reflects moderate variation, with values ranging from 17.2% to 99.3%. The negative skewness value (-1.1159) and kurtosis value (3.47) suggest that most countries emphasize Internet use, with only a few moderate outliers, reflecting a shift toward a more technology-oriented society. For the variable BankTrans, the low standard deviation of 3.1493, with the values ranging from -6.05 to 13.50, after log-transforming. However, the high kurtosis (-6.0504) and strong negative skewness indicate a sharply peaked distribution, with most countries having high mobile and internet banking transactions, while only a few have very low levels. This result further highlights significant disparities in the FinTech adoption across countries. Meanwhile, the variable Mobile has a mean of 121.9977 and a slightly higher standard deviation of 22.4764. The kurtosis value (3.0921) and near-zero skewness suggest a nearly normal distribution. It further implies that the mobile cellular subscriptions are relatively evenly distributed, and most countries have high penetration rates.

Furthermore, FDI, another key variable, shows a mean value of 3.2803. However, the notably high standard deviation of 22.4764, which ranges widely from -444.7069 to 431.7885, indicates there is high variation across the data. Additionally, FDI also has an extremely high kurtosis with a value of 73.1584, which further highlights large disparities in FDI inflow across countries, with a few countries experiencing minimal or negative inflows. Moving to economic performance indicators, the variable HFCE has a mean of 2.7794, with a standard deviation of 4.9794, indicating there is moderate variation of the household final consumption expenditure across countries. The kurtosis value

(5.1465) and the negative skewness (-0.4019) indicate a left-skewed and peaked distribution. This result further suggests that most of the countries are experiencing an increment growth in household consumption, while some report significantly low rates. Similarly, GDP growth has a mean value of 2.7341, suggesting moderate economic expansion across the sample countries. The high kurtosis of 8.5248 and negative skewness (-0.3437) indicate that most countries have moderate GDP growth, but with a few experiencing extreme negative or positive fluctuations.

Other than that, the variable Unemployment has a mean of 7.4869 with a standard deviation of 4.78, indicating relatively small differences between countries. The positive skewness (1.17) suggests that most countries have low or moderate unemployment rates, but a few countries have significantly higher rates. Meanwhile, the variable GFCF has a mean of 22.3450 and a standard deviation of 5.0495, considering a moderate variation of the data. Notably, the kurtosis and slightly positive skewness further suggest that this data contributes to an almost normal distribution, with a fair, consistent investment level across countries. On the contrary, the CO2 variable has a very high standard deviation of 28.6584, ranging from 0.6499 to 2069.5020. A leptokurtic and right-skewed distribution is further supported and reflected by the extremely high kurtosis and substantial positive skewness. It shows that while the majority of countries have comparatively low CO2 emissions, a small number of countries produce disproportionately large quantities.

Regarding the SDG, the overall SDG index has a mean of 73.7886, which indicates majority of countries have a satisfaction rating on sustainable development. However, the standard deviation (19.9484), ranging from 18.4250 to 99.9800, shows a high variance across countries. The kurtosis (2.5995) and slightly negative skewness (-0.5452) suggest that most countries perform relatively well in terms of sustainable development, with a few lagging behind with a lower score. In more detail, SDG1 has a mean of 88.6136 and a relatively high standard deviation of 19.9484, ranging from 18.4250 to 99.9800. It further indicates that there is a large variation in the poverty level of countries. Additionally, the kurtosis (6.9494) and negative skewness (-2.2086) indicate that a highly left-skewed and peaked distribution, which means that most countries have strong performance in poverty reduction, but some countries reported poor outcomes. SDG8, which refers to decent work and economic growth, has a mean of 73.8423 across countries. Among the SDG indices that were studied in this research, it has the lowest standard deviation of 6.7558, ranging from 46.8403 to 84.8729, showing the relatively different economic growth across countries. Furthermore, SDG 9 has the lowest mean of 60.7915, and the highest standard deviation (22.3312). It further suggests that there are large disparities in sustainability and development in industry, innovation, and infrastructure. However, the kurtosis and slightly positive skewness indicate that a near-normal distribution, where the variation across countries is still considered moderate and acceptable. Meanwhile, SDG 10 has a mean of 67.0816 and a standard deviation of 28.5059, with a minimum of 12.8170 and a maximum of 100. The results further show that some countries made a perfect effort in reducing inequalities, but some still lag behind. Similar to SDG 13, with a mean of 83.2748, indicating a high level of control in climate action across countries. However, it has a high standard deviation of 11.6842, ranging from 40.5267 to 98.8610, which further indicates that there is high variation across countries. For both SDG 10 and SDG 13, the negative skewness values of -0.5726 and -0.9901, respectively, indicate that while most countries perform well, there are still some that lag with relatively weak performance.

4.1.2 Comparison between Income Levels

4.1.2.1 FinTech development

Table 4.2: Descriptive Analysis of FinTech development by Income Level

Income Levels	**Variables**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**	**Kurtosis**	**Skewness**
	Startup	1	0.8165	0	2	0	1.75

Low Income	Internet	24.4857	6.1977	17.2000	34.2000	1.9276	0.4955
	BankTrans	6.8813	0.8119	6.0748	8.0970	1.7333	0.5239
	Mobile	80.0697	6.0599	72.2765	91.4623	3.0244	0.7345
Lower Middle Income	Startup	3.6071	5.1440	0	22	1.9828	6.5450
	Internet	47.0446	17.0689	21.5000	78.6000	1.7751	0.3263
	BankTrans	6.4933	5.1177	-6.0504	12.3104	4.4986	-1.5383
	Mobile	105.7412	23.0637	68.1001	146.1380	1.7401	-0.1085
Upper Middle Income	Startup	13.8016	22.514	0	112	2.6127	10.3562
	Internet	70.6833	14.0202	23.7000	97.7000	3.3033	-0.7256
	BankTrans	9.8898	2.9102	-3.0799	13.4961	11.5625	-2.7061
	Mobile	122.8175	25.5897	81.6619	181.2220	2.3584	0.4330
High Income	Startup	12.7551	14.0870	0	74	1.8583	6.3020
	Internet	86.3862	8.1736	60.0000	99.3000	3.3643	-0.7372
	BankTrans	10.9159	1.4139	4.1174	13.0766	11.6631	-2.6940
	Mobile	127.6129	15.8990	99.8304	180.8420	3.6773	0.7402

In the context of FinTech development, the variations in relevant indicators across different income levels are presented in Table 4.2: Descriptive Analysis of FinTech development by Income Level. Overall, the variables Internet, BankTrans, and Mobile generally exhibit an increasing pattern in mean values across income levels. It also indicates that the higher-income group has better access to the internet, banking, and mobile technologies, which represents a more advanced stage in the development of the FinTech industry. However, for the BankTrans variable, the lower middle-income countries have a slightly lower mean than the low-income countries, possibly due to the presence of outliers.

For the variable Startup, which refers to the number of FinTech startups, it has the highest mean and standard deviation for the upper-middle-income countries. It indicates that there is a rapid growth of FinTech startups, but with large disparities between countries. Meanwhile, for low- and middle-income countries, the data show a positive skewness, indicating that most countries are still at an early or underdeveloped stage of FinTech industry development, particularly in the upper-middle-income group. In contrast, high-income countries exhibit negative skewness, suggesting that most countries have a relatively large number of FinTech companies with stable growth, while only a few countries lag behind.

In more detail, the Internet has the highest standard deviation (17.0689) in the lower-middle-income group, ranging from 21.50 to 78.60. It suggests that high variation in the internet usage of the population in the lower-middle-income countries. In addition, the skewness of the Internet for the low-income and lower-middle-income countries exhibits a positive value, which means that a concentration of these countries with lower internet usage. In contrast, upper-middle-income and high-income countries show a negative skewness, indicating that most countries have high internet usage, but with some countries left behind.

Similarly, for the BankTrans, the lower middle-income countries have a high standard deviation (5.12), while others have low and moderate variability. The kurtosis has an extremely high value for both upper-middle-income and high-income countries, with the values of 11.56 and 11.66, respectively. It further indicates the distribution is sharply peaked, where most of the countries in the particular income levels are clustered near the means, with a few of the extremes.

For the Mobile, the variability is moderate across all income level groups. The upper-income countries have the highest standard deviation of 25.59, followed by lower-income countries of 23.06, reflecting diverse mobile cellular subscriptions in these countries. In terms of skewness, the variable has distinct results across income level groups. For the low-income, upper-middle-income income and high-income countries, it recorded a positive value, indicating some countries have very high mobile usage. Notably, the kurtosis of lower-middle-income countries of 1.74, showing the distribution is flatter with a wide spread of data.

4.1.2.2 Foreign Direct Investment

Table 4.3: Descriptive Analysis of FDI by Income Level

Income Levels	Variables	Mean	Standard Deviation	Minimum	Maximum	Kurtosis	Skewness
Low Income	FDI	2.6017	0.7869	1.5000	3.7995	1.9853	0.1069
Lower Middle Income	FDI	1.0294	5.2231	-30.2596	5.9939	24.6489	-4.2211
Upper Middle Income	FDI	3.3751	3.1398	-1.7016	17.1989	8.9552	2.2976
High Income	FDI	3.8866	60.0584	-444.7069	431.7885	37.5662	0.1380

The table above presents the FDI results in terms of variability and distribution across income-level groups, showing inconsistent patterns across different income levels. In terms of mean, the FDI variable fluctuates across income level groups, where the lower middle income has the lowest mean value of 1.0294. However, the standard deviation of high income is extremely high, with the value of 60.0584, ranging from -444.71 to 431.79. It further indicates that substantial fluctuations in FDI inflows among high-income countries across time and countries. For other income levels, the standard deviation has been recorded as low and moderate variability across the countries. Meanwhile, the high kurtosis value of lower middle income (24.65) and high income (37.57) indicates that the FDI distribution is highly peaked, with most observations concentrated around the mean and a few extreme values causing heavy tails. The skewness value of FDI also shows a considerable variation across income level groups. Notably, the lower middle-income countries have a strong negative skewness (-4.22), indicating most countries have higher FDI than the mean, but some with extremely low outliers. At the same time, the skewness of the variable for other income levels is all positive with slightly different values.

4.1.2.3 Economic Performance

Table 4.4: Descriptive Analysis of Economic Performance by Income Level

Income Levels	Variables	Mean	Standard Deviation	Minimum	Maximum	Kurtosis	Skewness
Low Income	HFCE	5.7061	5.0110	-0.9155	12.0867	1.4460	-0.0513
	GDP	6.5397	4.8600	-3.3737	10.8584	3.5396	-1.3646
	Unemployment	12.7014	1.9412	10.7590	15.7750	1.9358	0.7583
	GFCF	25.1105	1.7627	22.7137	26.9124	1.5286	-0.3531
	CO2	1.5245	0.1328	1.3093	1.6813	1.9443	-0.3184
Lower Middle Income	HFCE	3.4181	5.6125	-17.0821	16.8320	5.3887	-0.7549
	GDP	3.0953	7.8776	-20.5416	31.9619	7.1042	0.1451
	Unemployment	7.6491	5.7069	1.1610	18.3990	1.9818	0.7189
	GFCF	22.1442	7.4783	9.6504	32.9448	1.6837	-0.1226
	CO2	63.3341	105.1677	0.6499	372.9485	5.4617	1.9559
Upper Middle Income	HFCE	3.3700	5.5658	-15.3181	18.8991	4.9410	-0.5447
	GDP	2.8886	4.9242	-14.5465	14.0124	4.4069	-0.8354
	Unemployment	8.3062	5.9410	0.7160	23.6150	2.8255	0.8081
	GFCF	22.2469	4.7173	13.6094	32.3469	2.3290	0.1767
	CO2	164.3443	201.3042	3.7547	674.5359	2.5303	0.9846
High Income	HFCE	2.1128	4.2679	-12.2592	20.8394	5.1974	-0.3032
	GDP	2.3957	4.0767	-17.8212	16.4671	6.8641	-0.8954
	Unemployment	6.7277	3.3149	2.0150	21.4130	6.5602	1.7341
	GFCF	22.3667	4.4478	10.9705	39.3363	4.7994	0.6579
	CO2	156.9170	364.8656	6.5511	2069.5020	19.9090	4.1117

In the context of economic performance, the mean of HFCE and GDP both has decreasing patterns with the income levels. These results indicate that as countries move toward higher income categories, the relative growth of household consumption and GDP tends to stabilize. In contrast, the CO2 has an increasing mean value with the income levels, indicating that higher-income countries tend to produce more emissions. This may be attributed to greater industrial activity, higher energy consumption, and the expansion of production and transportation sectors associated with advanced economic development. For the Unemployment and GFCF, there is a variation in the mean, but with consistency of the highest mean value in low-income countries. This reflects the structural challenges faced by low-income economies, such as limited job opportunities, lower investment efficiency, and unstable capital formation.

Specifically, the standard deviation of HFCE across all income level countries is considered high, especially for upper-middle-income countries (5.5658). The variability suggests that considerable differences in HFCE exist across countries, possibly due to uneven income distribution, diverse consumption patterns, and different levels of economic development. Meanwhile, the kurtosis values are high for lower-middle-income (5.3887), upper-middle-income (4.9410), and high-income (5.1974) countries, except for the low-income countries (1.4460). The high kurtosis reflects that the distribution for those income levels is more leptokurtic. Additionally, the negative skewness further indicates that most observations are above the mean, with a few low outliers.

For GDP, the standard deviation also remains high for the lower middle income (7.8776), upper middle income (4.9242), and high income (4.1767), indicating there are disparities in the annual growth performance. Notably, all income level countries have relatively high kurtosis, except low-income countries. For upper-middle-income and high-income countries, the high kurtosis and negative skewness indicate that most countries have moderate growth, with a few countries reporting significantly low GDP.

Furthermore, Unemployment generally decreases with the income levels, which is consistent with a stronger labor market in more developed markets. The standard deviation in the lower-middle-income (5.7069) and upper-middle-income (5.9410) countries is also relatively high, indicating uneven labor market performance in these particular income level countries. In addition, the skewness for all income levels was recorded as a positive value, suggesting that most countries have low unemployment rates, while a few have exceptionally high rates.

Similarly, GFCF also has a relatively high standard deviation for the lower-middle and upper-middle income countries. These results reflect greater disparities in investment activities and capital formation within these groups. Different from other variables, GFCF has a moderate kurtosis and near-zero skewness, which further indicates that the distribution is relatively balanced with few outliers.

On the contrary, the standard deviation of CO_2 is exceptionally high across most income levels, except for low-income countries, suggesting greater variability in emissions among more industrialized economies. These results further highlight the disparities in emission intensity. Significantly, the high-income countries have a very high kurtosis (19.9090) and strong positive skewness (4.1117), which is different from other income level countries. It further shows that most countries have moderate emissions, while a few have exceptionally high emissions, which largely influence the distribution.

4.1.2.4 Sustainable Development Goals

Table 4.5: Descriptive Analysis of SDG by Income Level

Income Levels	**Variables**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**	**Kurtosis**	**Skewness**
Low Income	SDGIndex	60.2826	1.2937	58.4240	61.8997	1.6453	-0.1448
	SDG1	21.2571	2.5565	18.4250	25.7540	2.3616	0.8366
	SDG8	73.0755	1.3279	71.3834	75.6774	3.4090	0.9329
	SDG9	31.7989	2.9892	27.9824	36.7006	2.1466	0.4727

	SDG10	34.9015	0.0000	34.9015	34.9015	-	-
	SDG13	98.5457	0.1924	98.3567	98.8610	1.8707	0.4816
Lower Middle Income	SDGIndex	63.5090	5.9950	54.7869	73.1039	1.9002	0.2046
	SDG1	59.8143	26.7348	20.0365	97.6400	1.6510	0.0929
	SDG8	67.6533	8.4824	46.8403	80.1253	3.4224	-1.0149
	SDG9	35.3878	9.7229	20.8988	55.5580	1.9304	0.3704
	SDG10	53.9460	27.8329	19.1550	93.5290	1.2834	0.0946
	SDG13	95.7897	2.3281	89.9887	97.9620	3.3184	-1.2557
Upper Middle Income	SDGIndex	70.3838	4.4457	58.6579	79.7251	3.5729	-0.6662
	SDG1	89.2563	10.7175	58.6060	98.9735	3.6158	-1.2144
	SDG8	70.6939	5.5923	60.3973	80.5239	1.8161	0.0063
	SDG9	47.1639	11.3708	22.2505	77.4221	3.0943	0.2578
	SDG10	54.2975	27.4651	12.8170	100.0000	1.7332	0.0625
	SDG13	88.3575	9.0094	50.9103	96.2890	11.6163	-2.9931
High Income	SDGIndex	79.3968	4.0723	67.7271	87.0992	3.4277	-0.6305
	SDG1	98.8344	1.3747	92.2495	99.9800	12.4283	-3.0448
	SDG8	77.6620	4.1703	64.4430	84.8729	3.1744	-0.8554
	SDG9	77.8457	15.6321	39.6383	99.6504	2.2248	-0.2491
	SDG10	80.2023	23.0819	17.0425	100.0000	4.7487	-1.6606
	SDG13	75.8862	9.5061	40.5267	93.5797	5.3691	-1.0762

In the context of sustainable development goals, the mean values exhibit a generally increasing pattern with higher income levels, except for SDG 8 and SDG 13, which deviate from this pattern. It further shows that the higher the income levels, the greater the score achieved in terms of sustainability. In detail, the mean value of the overall SDG Index shows a clear increasing trend across income levels, further supporting the relationship between higher income levels and greater progress toward sustainable development goals. In contrast, SDG 13 exhibits a decreasing trend across income levels, indicating that sustainable performance in terms of climate action tends to be relatively weaker in higher-income countries. These patterns further demonstrate that environmental degradation is a cost of economic growth as economies move from low to high income levels. However, SDG 8 shows a more fluctuating mean across income levels, with the lowest value observed in lower-middle-income countries. This suggests that progress in decent work and economic growth is uneven, with lower-middle-income countries potentially facing challenges in economic growth compared to other income groups.

Specifically, SDG 1, which refers to no poverty, has a low and stable standard deviation for the low-income and high-income countries. In contrast, the lower middle-income and higher middle-income countries have reported a high variability, with the values of 26.7348 and 10.7175, respectively. It further suggests that an uneven performance in poverty reduction among the middle-income countries is possibly due to economic structure, social protection coverage, institutional capacity, and the varying levels of vulnerability faced by their populations. Additionally, the skewness value shifts from positive to negative from low income to high income, which also supports the argument that high income countries with higher capability in poverty reduction, while some are still lagging.

For SDG 8, the lower middle-income countries have the highest standard deviation with the lowest mean value. It means that there is high variability for the lower-middle-income countries, showing the uneven and weak performance in decent work and economic growth, which might be due to limited industrialization and informal employment. In addition, the negative skewness of middle- and high-income levels shows that most countries perform relatively well, but with a few weaker outliers.

As mentioned above, SDG 9 shows a strong increasing pattern with income levels. However, the standard deviation for SDG 9 is also increasing sharply across income levels, especially in high-income countries (15.6321). These circumstances might have occurred due to the large variation in innovation and infrastructure development, even in high-income countries. Notably, the skewness of high-income levels has turned into a negative value, which shows that most countries perform well, but a few lag behind. In contrast, the skewness is positive and low for low- and middle-income levels, showing that most of the countries are underperforming, but only with some strong performance.

Notably, SDG 10 shows no variation within the low-income group, as only a single country is represented in this category. Consequently, the reduced inequalities score remains constant and produces a standard deviation of zero. For other income levels, the standard deviation of SDG 10 is relatively high, implying strong heterogeneity across all countries. Meanwhile, the high income has the only negative skewness among income levels, which further suggests that most countries perform well, with only some countries having a lower score in reduced inequalities.

Different from others, SDG 13 has a decreasing pattern, which aligns with the concept that higher-income countries often have higher emissions and environmental pressure due to industrialization. The high kurtosis and negative skewness, especially for upper-middle-income and high-income countries, further suggest that higher-income-level countries mostly perform well, but some countries perform extremely poorly. his disparity ultimately affects the overall distribution of climate action performance within these income groups and highlights the uneven progress toward SDG 13.

4.2 Research Question 1

To evaluate Research Question 1, which examines whether FinTech development differs across income levels, the diagnostic checks and the Kruskal–Wallis test results are presented below.

4.2.1 Diagnostic Check Results

To ensure the reliability of the inferential statistics comparing income levels, the detailed results of the diagnostic checks are reported as follows:

4.2.1.1 Normality

Table 4.6: Summary of Normality results: Shapiro-Wilk Test

Variable	**p-value > z**			
	Low Income	**Lower Middle Income**	**Upper Middle Income**	**High Income**
Startup	0.99984	0.00000	0.00000	0.00000
Internet	0.56420	0.00152	0.00055	0.00001
BankTrans	0.21690	0.00000	0.00000	0.00000
Mobile	0.52099	0.01118	0.00039	0.00005

To assess the normality of the data, the Shapiro–Wilk test was applied to the FinTech development measurements. Based on Table 4.6, the p-values for lower-middle-income, upper-middle-income, and high-income countries are all less than 0.05, indicating that the data for these groups deviate significantly from a normal distribution. In contrast, the p-value for low-income countries is greater than 0.05, suggesting that the data for this group do not differ significantly from normality. Consequently, since the data for most income groups deviate from normality, the normality assumption for ANOVA is not satisfied.

4.2.1.2 Homogeneity of Variance

Table 4.7: Summary of Homogeneity of Variance Results: Barlett's equal variance test

Variable	p-value	Interpretation
Startup	0.000	Variances are not equal (Heterogeneity)
Internet	0.000	Variances are not equal (Heterogeneity)
BankTrans	0.000	Variances are not equal (Heterogeneity)
Mobile	0.000	Variances are not equal (Heterogeneity)

At the same time, Bartlett's test for equal variances was conducted to assess the homogeneity assumption required for ANOVA. As shown in Table 4.7, the p-values for the four variables, which are Startup Internet, BankTrans, and Mobile, are all 0.000, indicating that the null hypothesis of equal variances can be rejected. Therefore, the variances are unequal, demonstrating heteroscedasticity. Meanwhile, it also violates the homogeneity assumption of ANOVA.

Since both the normality and homogeneity assumptions for ANOVA are violated, the non-parametric Kruskal–Wallis test is employed to examine differences in FinTech development across income levels.

4.2.2 Kruskal-Wallis Test Results

Table 4.8: Summary of Kruskal-Wallis Test Results

Variable	H (χ^2)	p-value	Results
Startup	47.047	0.0001	Significant
Internet	209.866	0.0001	Significant
BankTrans	86.819	0.0001	Significant
Mobile	50.493	0.0001	Significant

Based on Table 4.8, all FinTech development variables, which are Startup, Internet, BankTrans, and Mobile, show statistically significant results, with p-values of 0.0001. Therefore, it is sufficient evidence to reject the null hypothesis, indicating that at least one pair of the income level groups has a significant difference in the median indicator of Fintech development. These results are also consistent with hypothesis 1, which supports that the development of the FinTech industry varies across different income level countries. Furthermore, a post-hoc analysis with the Dunn test was conducted to evaluate the detailed differences in FinTech development across groups. A total of six pairwise comparisons, as shown in Table 4.9 below.

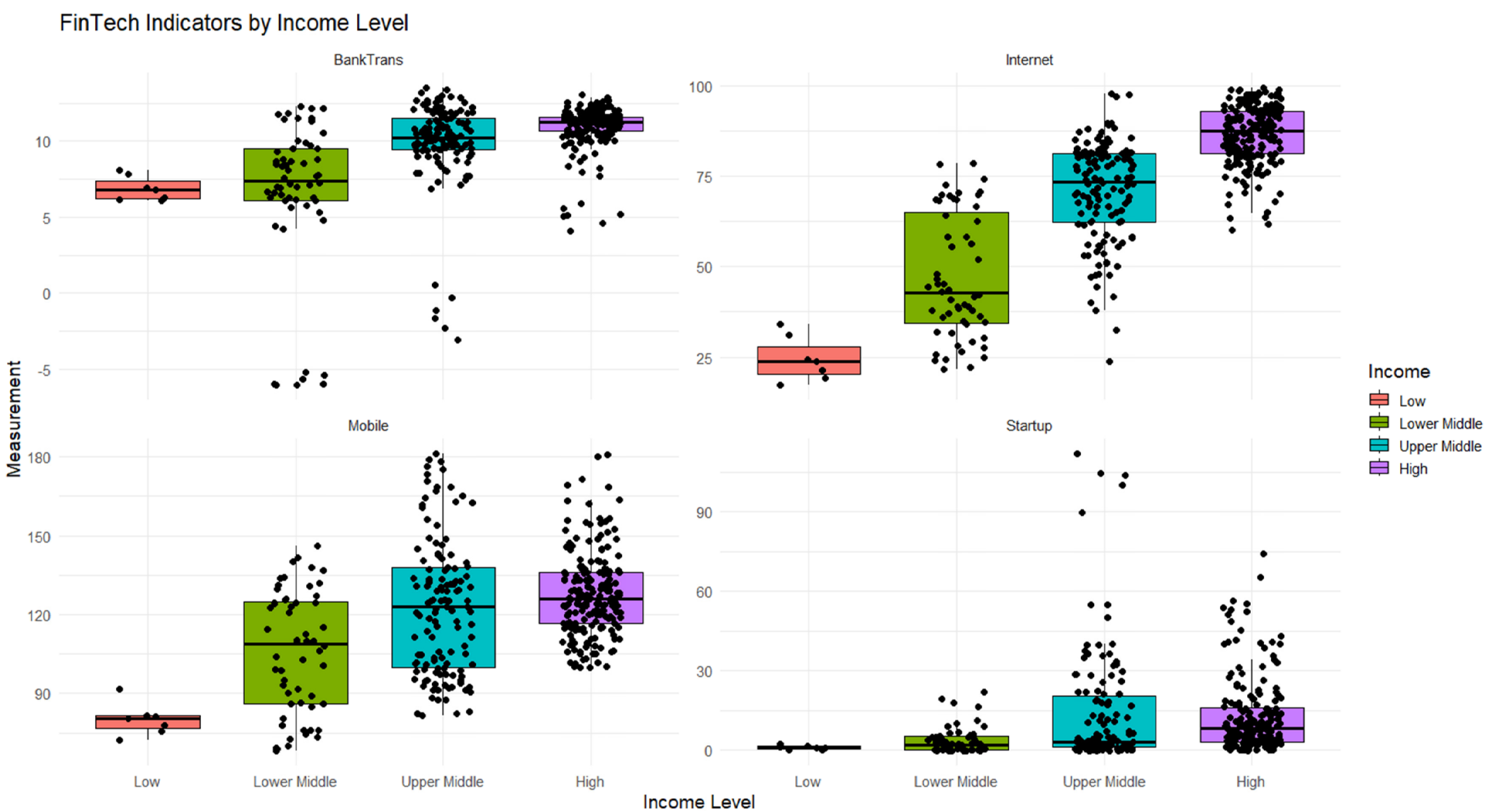
Table 4.9: Summary of Dunn Test Results

Comparison	**Median differences**	**p-value**	**Results**
(i) Startup			
Lower Middle Income vs. Low Income	-1.0292	0.9102	No Significant
Upper Middle Income vs. Low Income	-2.4557	0.0410	Significant
Upper Income Middle Income vs. Lower Middle Income	-3.3927	0.0021	Significant
High Income vs. Low Income	-3.4608	0.0016	Significant
High Income vs. Lower Middle Income	-6.0626	0.0000	Significant
High Income vs. Upper Middle Income	-3.2730	0.0032	Significant
(ii) Internet			
Lower Middle Income vs. Low Income	-1.0707	0.8529	No Significant
Upper Middle Income vs. Low Income	-3.2274	0.0037	Significant
Upper Income Middle Income vs. Lower Middle Income	-5.1308	0.0000	Significant
High Income vs. Low Income	-6.0268	0.0000	Significant
High Income vs. Lower Middle Income	-12.4668	0.0000	Significant
High Income vs. Upper Middle Income	-9.3266	0.0000	Significant

(iii) BankTrans			
Lower Middle Income vs. Low Income	-1.1308	0.7745	No Significant
Upper Middle Income vs. Low Income	-3.2450	0.0035	Significant
Upper Income Middle Income vs. Lower Middle Income	-5.0235	0.0000	Significant
High Income vs. Low Income	-4.4930	0.0000	Significant
High Income vs. Lower Middle Income	-8.4141	0.0000	Significant
High Income vs. Upper Middle Income	-4.0998	0.0001	Significant
(iv) Mobile			
Lower Middle Income vs. Low Income	-2.4208	0.0465	Significant
Upper Middle Income vs. Low Income	-4.0842	0.0002	Significant
Upper Income Middle Income vs. Lower Middle Income	-3.7598	0.0005	Significant
High Income vs. Low Income	-4.7571	0.0000	Significant
High Income vs. Lower Middle Income	-5.6715	0.0000	Significant
High Income vs. Upper Middle Income	-2.2377	0.0757	No Significant

Overall, FinTech development shows an increasing trend with income level, particularly in Startup, Internet, BankTrans, and Mobile. Most of the pairwise comparisons are significant, where p-values are less than 0.05, confirming differences across income groups. While none of the indicators show significance in all comparisons, the general increasing patterns remain clear. Notably, Startup, Internet, and BankTrans show no significant difference between low- and lower-middle-income economies, suggesting similar development within low-income countries. However, it is notable that the comparisons involving the low-income group may be subject to bias, given that Rwanda is the only country representing this category. Conversely, Mobile shows no significant difference between upper-middle- and high-income economies, indicating a plateau at higher income levels.

Figure 4.1: Boxplot of FinTech development by income levels



4.3 Research Question 2

To further examine the relationship between FinTech development and FDI, as outlined in Research Question 2, the processes and results of the diagnostic checks, model selection, and regression analysis are presented below.

4.3.1 Model Selection

Table 4.10: Summary of Model Selection Tests Results of RQ2

	Breusch-Pagan LM Test	**Redundant Fixed Effects Test**	**Hausman Test**	
Dependent Variable	**p-value**	**p-value**	**p-value**	**Results**
FDI	1.000	0.5443	-	Pooled OLS is preferred

In the model selection, the first test conducted is the Breusch-Pagan Lagrange Multiplier (LM) test, used to detect the presence of random effects. Based on Table 4.10, the p-value of the test is 1.000, indicating that Pooled OLS is sufficient for the estimation. In addition, the Redundant Fixed Effects test further supports this, with a p-value of 0.5443, suggesting that the use of Pooled OLS is more appropriate than a Fixed Effects model. As supported by both tests, the Hausman Test is not required. In summary, Pooled OLS is preferred for this model, as neither random effects nor significant heterogeneity is detected.

4.3.2 Diagnostic Check Results

To ensure the reliability of the estimated regression results, the detailed results of the diagnostic checks are reported as follows:

4.3.2.1 Unit Root Test

Table 4.11: Summary of Unit Root Test Results of RQ2

Variable	p-value [inverse chi-squared (110)]	Results
Startup	0.0000	Stationery
Internet	0.0000	Stationery
BankTrans	0.0000	Stationery
Mobile	0.0000	Stationery

The first diagnostic test conducted is the unit root test, using the Augmented Dickey–Fuller (ADF) method at level. Based on Table 4.11, all independent variables, representing FinTech development measurements, show p-values of 0.0000. Therefore, there is sufficient evidence to reject the null hypothesis of a unit root, indicating that all variables are stationary. This confirms that the stationarity assumption required for Pooled OLS is satisfied.

4.3.2.2 Multicollinearity

Table 4.12: Summary of the Multicollinearity Test of RQ2

Variable	Vif	Results
Startup	1.63	No multicollinearity
Internet	1.45	No multicollinearity
BankTrans	1.19	No multicollinearity
Mobile	1.06	No multicollinearity

Furthermore, the multicollinearity test using the variance inflation factor is used to identify whether the independent variables in the regression model are highly correlated. Based on Table 4.12, it shows that the VIF values are all below 5, indicating that there is no significant multicollinearity among the independent variables, which are Startup, Internet, BankTrans, and Mobile. This suggests that the regression coefficients are reliable and the individual effects of the FinTech development variables can be interpreted with confidence.

4.3.2.3 Heteroskedasticity

Table 4.13: Summary of Heteroskedasticity results of RQ2

Tests	**χ^2(df)**	**p-value**	**Results**
Breusch–Pagan test	4.18 (1)	0.0409	Heteroskedasticity detected
White's test	32.98 (9)	0.0029	Heteroskedasticity detected

To examine the presence of heteroskedasticity, two tests were conducted, which are Breusch–Pagan test and White's test. Both tests assess whether the assumption of constant variance of residuals is satisfied in the regression model. The results, presented in Table 4.13, show p-values of 0.0409 and 0.0029, respectively, indicating that the null hypothesis of homoskedasticity is rejected. Therefore, heteroskedasticity is present in the model. To address the heteroskedasticity problem, cluster robust standard errors will be applied in the model to correct for the non-constant variance of residuals. This adjustment ensures that the coefficient estimates remain unbiased while producing valid standard errors and significance tests.

4.3.2.4 Autocorrelation

Table 4.14: Summary of Autocorrelation Results of RQ2

Test	**F-statistics**	**p-value**	**Results**
Wooldridge Test	0.163	0.6882	No Autocorrelation detected

Based on the Wooldridge Test in Table 4.14, the p-value is more than 0.05, which indicates that there is no autocorrelation detected in the model. This result indicates that the assumption of no serial correlation is met, and the regression results are considered reliable because the error terms are not related over time.

4.3.3 Regression Analysis

Table 4.15: Regression Results of RQ2

Statistics	**Dependent Variable: FDI**
Adjusted R-Squared	0.0010
F-statistic (p-value)	0.5900 0.6735
Startup Coefficient t-statistic (p-value)	 0.0305 0.4400 0.6630
Internet Coefficient t-statistic (p-value)	 -0.0371 -0.3300 0.7430
BankTrans Coefficient t-statistic (p-value)	 -0.1958 -0.2300 0.8170
Mobile Coefficient t-statistic (p-value)	 0.0523 0.8000 0.4290
Constant Coefficient t-statistic (p-value)	 1.2461 0.15 0.878

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

After the diagnostic checks and model selection, the regression results using Pooled OLS with cluster-robust standard errors are presented in Table 4.3.7. Based on the results, the adjusted R-squared is 0.0010, indicating that only 0.10% of the variation in FDI inflow is explained by FinTech development. Additionally, the overall model is not statistically significant, with a p-value of 0.6735, which is higher than the 0.05 significance level. Similarly, the significance levels for all FinTech development variables, which are Internet, BankTrans, and Mobile, are above 0.05, indicating that none of these variables are statistically significant in explaining changes in FDI inflows.

In more detail, the Internet and BankTrans have a negative relationship with FDI, with the value of -0.0371 and -0.1958, respectively. Other than that, Startup and Mobile have a positive coefficient value of 0.0305 and 0.0523, respectively. It further indicates that the increasing number of Fintech startups and higher mobile subscriptions are contributing to a slight increase in FDI. However, it is notable that these effects of the FinTech development are not statistically meaningful.

These results contradict the International Investment Location Theory, which argues that stronger and more efficient financial systems should enhance a country's attractiveness to foreign investors, thereby increasing FDI inflows. On the other hand, it is consistent with Institutional Theory, which argues that the current adoption of FinTech is largely driven by global pressure and uncertainty, and may not yet be sufficient to create significant changes in FDI inflows. In addition, past research has reported conflicting findings. Therefore, the insignificant result in this study is consistent with the studies of Uddin et al. (2024) and Jiang et al. (2024), while contradicting the study of Al-Smadi &Al-Smadi (2024). Specifically, this insignificant result strongly aligns with Jiang et al. (2024), who argue that market reactions to FinTech development are temporary and generate only limited effects.

4.4 Research Question 3

In Research Question 3, which examine the relationship between FDI and economic performance, with the moderate effect of income levels. Therefore, the following diagnostic check and regression, FDI is multiplied by an ordinal income-level variable (1 = low-income to 4 = high-income) to estimate how the effect of FDI on macroeconomic variables varies with income. The dependent variables, which are economic performance indicators included in this analysis, are HFCE, GDP, Unemployment, GFCF, and CO_2 emissions. The detailed diagnostic checks, model specification, and regression results for the five models are presented below. Since the models include a moderating effect with the interaction term, mean centering is applied to the continuous independent variables to reduce the multicollinearity that naturally arises between the main effects and their interaction term.

4.4.1 Model Selection

Table 4.16: Summary of Model Selection Tests Results of RQ3

	Breusch-Pagan LM Test	**Redundant Fixed Effects Test**	**Hausman Test**	
Variable	**p-value**	**p-value**	**p-value**	**Results**
HFCE	1.000	0.8453	-	Pooled OLS is preferred
GDP	1.000	0.3539	-	Pooled OLS is preferred
Unemployment	0.0000	0.0000	0.8221	REM is preferred
GFCF	0.0000	0.0000	0.9217	REM is preferred

CO2	0.0000	0.0000	0.9980	REM is preferred

In the model selection, the results varied across the five models, which further determined the selected model for each. Based on Table 4.16, the models with HFCE and GDP as the dependent variables consistently indicate that Pooled OLS is the preferred estimation method. The Breusch–Pagan LM Test reports p-values of 1.00 for both models, suggesting that the REM is not suitable and supporting the use of Pooled OLS. Additionally, when comparing Pooled OLS with the fixed effects model, the p-values in the Redundant Fixed Effects Test show 0.7152 and 0.9943, respectively, which further reinforces that Pooled OLS is the appropriate choice for these two models. On the contrary, the models with Unemployment, GFCF, and CO2 also have consistent results, where the REM is the preferred estimation method. For the three models, both the Breusch–Pagan LM Test and the Redundant Fixed Effects Test report consistent p-values of 0.0000, indicating that Pooled OLS is not suitable for these models. Therefore, the Hausman Test is conducted to determine whether the FEM or REM is more appropriate. Since the p-values for all three models are above 0.05, the results suggest that REM is the preferred estimation method.

4.4.2 Diagnostic Check Results

To ensure the reliability of the estimated regression results, the detailed results of the diagnostic checks are reported as follows:

4.4.2.1 Unit Root Test

Table 4.17: Summary of Unit Root Test Results of RQ3

Variable	**p-value [inverse chi-squared (110)]**	**Results**

FDI	0.0000	Stationery
INFDI	0.0000	Stationery

Based on Table 4.17, the p-value of FDI in the Augmented Dickey-Fuller test is reported as 0.0000, indicating that the series is stationary. This fulfills the first requirement of the regression model, ensuring that the estimates are reliable in terms of avoiding spurious relationships.

4.4.2.2 Multicollinearity

Table 4.18: Summary of the Multicollinearity Test of RQ3

	VIF				
Variable	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**
INFDI	41.85	41.85	41.85	41.85	41.85
FDI	41.85	41.85	41.85	41.85	41.85
Income Level	1.07	1.07	1.07	1.07	1.07

In these five regression models, the independent variables are the same; therefore, the VIF results are also identical across all models. Based on Table 4.18, the VIF value for the FDI and the interaction term of FDI and income level is extremely high. However, this inflation is expected when interaction terms are included. The INFDI, is constructed directly from FDI; therefore, these two variables are naturally highly correlated, which results in inflated VIF values. In contrast, the VIF for the income level remains normal even though it is part of the interaction term. This is because income level is a categorical dummy variable, and dummy variables do not vary continuously. As a result, their correlation with the interaction term is much smaller, keeping the VIF value at an acceptable level. Therefore, the high VIF can be safely ignored in this context.

4.4.2.3 Heteroskedasticity

Table 4.19: Summary of Heteroskedasticity results of RQ3

	Breusch–Pagan test		**White's test**		
Dependent Variable	**χ^2(df)**	**p-value**	**χ^2(df)**	**p-value**	**Results**
HFCE	2.37	0.1237	13.11	0.1083	Homoskedasticity
GDP	157.53	0.0000	76.04	0.0000	Heteroskedasticity

In the diagnostic check for heteroskedasticity, only the models with HFCE and GDP as the dependent variables were tested, because these models were selected as the preferred specification under Pooled OLS. For the remaining models that were estimated using the random effects approach, the heteroskedasticity test is not applicable. This is because, at the model selection stage, the presence of random effects was confirmed, and heteroskedasticity is handled differently under the random effects framework. As a result, the conventional heteroskedasticity test used for Pooled OLS does not apply to REM.

Based on Table 4.19, the model with HFCE is free from the heteroskedasticity issues, as p-values are more than 0.05 for both Breusch-Pagan and White tests. In contrast, the model with GDP as a dependent variable has a p-value of 0.0000 for both tests, indicating the model suffered from the heteroskedasticity issue. Therefore, the assumption of constant variance among residuals is violated. For the model that was estimated using a random effect approach, the random effects estimator itself also partially accounts for variance differences across individuals, further mitigating the impact of heteroskedasticity.

To address the potential heteroskedasticity issue, cluster-robust standard errors were applied to the model with GDP as the dependent variable, and also to the other models estimated using the random effects approach. By using this method, the standard errors are adjusted to account for heteroskedasticity and within-panel correlation, providing more reliable inference.

4.4.2.4 Autocorrelation

Table 4.20: Summary of Autocorrelation Results of RQ3

Dependent Variable	**F-statistics**	**p-value**	**Results**
HFCE	0.093	0.7618	No Autocorrelation detected
GDP	0.472	0.4950	No Autocorrelation detected
Unemployment	46.318	0.0000	Autocorrelation detected
GFCF	61.006	0.0000	Autocorrelation detected
CO2	63.446	0.0000	Autocorrelation detected

In the Wooldridge Test, the results for autocorrelation vary across the five models, as presented in Table 4.20. For the models with HFCE and GDP as the dependent variables, the p-values are 0.7618 and 0.4950, respectively, both above 0.05. These results indicate that no autocorrelation is detected in these models. In contrast, the models with Unemployment, GFCF, and CO_2 as dependent variables all have p-values of 0.000, indicating the presence of autocorrelation. Therefore, the assumption of no autocorrelation is violated for these three models, which could lead to biased standard errors and unreliable significance tests. To address this issue, a similar approach, cluster-robust standard errors, is applied to ensure that the coefficient estimates remain unbiased and the inference is reliable.

After considering all the diagnostic results, the HFCE model does not require any remedial measures, as it satisfies all the regression assumptions. For the remaining models, cluster-robust standard errors will be applied to address heteroskedasticity and autocorrelation, since these models exhibited at least one of the issues identified in the diagnostic tests.

4.4.3 Regression Analysis

Table 4.21: Regression Results of RQ3

	Dependent Variable				
Statistics	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**
Adjusted R-Squared	0.0337	0.0379	0.0248	0.0303	0.0109
F-statistic (p-value)	4.43 0.0045	11.91 0.0000	57.84 0.0000	258.06 0.0000	5.02 0.1702
FDI Coefficient t-statistic (p-value)	 0.0758** 2.01 0.046	 -0.1025 -1.22 0.229	 -0.0082 -0.49 0.623	 0.1593*** 14.61 0.000	 -0.0402 -0.81 0.418
Income Level Coefficient t-statistic (p-value)	 -1.0297*** -3.13 0.002	 -0.3397 -0.67 0.507	 -0.9466 -1.24 0.217	 -0.4581 -0.52 0.602	 38.5455 0.93 0.350
INFDI Coefficient t-statistic (p-value)	 -0.0994* -1.77 0.077	 0.1694 1.35 0.182	 0.0145 0.59 0.557	 -0.2367*** -14.71 0.000	 0.0626 0.85 0.397
Constant Coefficient t-statistic (p-value)	 2.8451 11.24 0.000	 2.6222 10.00 0.000	 7.4774 12.19 0.000	 22.5014 35.74 0.000	 142.869 3.64 0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.21, the regression results for all five models are presented. The results vary across models, reflecting different relationships and significance levels between FDI and various measures of economic performance.

For the first model, with HFCE as the dependent variable, the R-squared is 0.0337, indicating that only 3.37% of the variation in HFCE is explained by the model. Although the explanatory power is very low, the overall model is still statistically significant, as the results of the F statistic (4.43) and p-value (0.0045), at the 1% significance level. In detail, the positive coefficient of FDI ($\beta = 0.0758$) indicates that a one-unit increase in FDI will increase HFCE by 0.0758 units at the average level, holding all other variables constant. In addition, the effect is statistically significant. Similarly, income level also has a highly significant effect on HFCE, with a negative coefficient ($\beta = -1.0297$, $p = 0.002$), indicating that higher income levels are associated with lower HFCE in the model. In addition, there is a moderating effect with marginal significance at the 10% level. This further indicates that Income Level weakens the FDI-HFCE relationship.

The model with GFCF as the dependent variable has a low explanatory power, where only 3.03% of the variation in GFCF is explained by the model. However, the model is still statistically significant, with a p-value of 0.0000. For the individual effects, FDI is highly significant ($p = 0.000$) with a positive coefficient ($\beta = 0.1593$), showing that an increase in FDI corresponds to an increase in GFCF by 0.1593 units at the average level, holding other variables constant. Similar to the INFDI, with a p-value of 0.000, indicating a moderating effect of income level for the relationship between FDI and GFCF. The negative coefficient of INFDI ($\beta = -0.2367$) further suggests that the positive effects of FDI on GFCF decrease as the income level increases. In contrast, the p-value for Income Level is greater than 0.05, indicating that Income Level alone does not have a statistically significant effect on GFCF.

On the contrary, in the model with GDP, Unemployment, and CO2 as the dependent variables, the explanatory power of this model is relatively low, indicating limited ability to explain the variation. Furthermore, none of the variables of these models is statistically significant, and the interaction term also shows no evidence of a moderating effect. This suggests that FDI and Income Level do not have a detectable influence on GDP, Unemployment, and CO2.

In short, FDI can only be significant and positively contribute to specific components of macroeconomic performance, which are HFCE and GFCF. However, it is notable that the effect of FDI on overall growth is limited, especially for GDP, Unemployment, and CO2. The significant effect of FDI on HFCE and GFCF is consistent with the FDI-Growth Spillover Theory, whereas the insignificant effects on other macroeconomic indicators align with the Absorptive Capacity Hypothesis. Past studies have often reported mixed results across countries (Mahmoodi & Mahmoodi, 2016; Bermejo Carbonell & Werner, 2018), which may partly explain the low coefficients in this model. Specifically, the regression results for HFCE and GFCF align with the findings of Alvarado et al. (2017), Luo, Sun, and Zhou (2022), and Ochirova and Miriakov (2025). Although FDI is not statistically significant for GDP, Unemployment, and CO2, these results contradict the studies mentioned above but are consistent with Azman-Saini et al. (2010), Alvarado et al. (2017), Mahmoodi & Mahmoodi (2016), and Uddin et al. (2024).

4.5 Research Question 4

In Research Question 4, the focus is on examining the mediating effect of FDI. Accordingly, three models were constructed for each economic performance variable, which are the total effect of FinTech development, the total effect of FDI, and the direct effect of FDI on economic performance. Additionally, for the moderating effect, there is an interaction term of the FinTech development and income level. Besides, it is important to note that the total effect of FDI has already been discussed in Section 4.5, which addresses Research Question 3. Therefore, in this section, only the diagnostic checks and regression analyses of the total effect of FinTech development and the direct effect of FDI on economic performance, and the comparison of the three models will be presented. Similarly, mean-centering is applied to all models, as each includes an interaction term that may otherwise introduce multicollinearity issues.

4.5.1 Model Selection

Table 4.22: Summary of Model Selection Tests Results of RQ4

	Breusch-Pagan LM Test	**Redundant Fixed Effects Test**	**Hausman Test**	
Variable	**p-value**	**p-value**	**p-value**	**Results**
<u>(i) Total Effect</u>				
DV: HFCE				
Startup	1.0000	0.8851	-	Pooled OLS is preferred
Internet	1.0000	0.9088	-	Pooled OLS is preferred
BankTrans	1.0000	0.8775	-	Pooled OLS is preferred
Mobile	1.0000	0.6810	-	Pooled OLS is preferred
DV: GDP				

Startup	1.0000	0.9961	-	Pooled OLS is preferred
Internet	1.0000	0.9970	-	Pooled OLS is preferred
BankTrans	1.0000	0.9942	-	Pooled OLS is preferred
Mobile	1.0000	0.9823	-	Pooled OLS is preferred
DV: Unemployment				
Startup	0.0000	0.0000	0.4998	REM is preferred
Internet	0.0000	0.0000	0.4427	REM is preferred
BankTrans	0.0000	0.0000	0.9714	REM is preferred
Mobile	0.0000	0.0000	0.5144	REM is preferred
DV: GFCF				
Startup	0.0000	0.0000	0.3518	REM is preferred
Internet	0.0000	0.0000	0.5167	REM is preferred
BankTrans	0.0000	0.0000	0.4330	REM is preferred
Mobile	0.0000	0.0000	0.0452	FEM is preferred
DV: CO2				
Startup	0.0000	0.0000	0.036 (Sargan Hansen Test)	FEM is preferred
Internet	0.0000	0.0000	0.8966	REM is preferred
BankTrans	0.0000	0.0000	0.7805	REM is preferred
Mobile	0.0000	0.0000	0.1041 (Sargan Hansen Test)	REM is preferred
(ii) Direct Effect				

DV: HFCE				
Startup	1.0000	0.9023	-	Pooled OLS is preferred
Internet	1.0000	0.9239	-	Pooled OLS is preferred
BankTrans	1.0000	0.8897	-	Pooled OLS is preferred
Mobile	1.0000	0.6981	-	Pooled OLS is preferred
DV: GDP				
Startup	1.0000	0.9979	-	Pooled OLS is preferred
Internet	1.0000	0.9983	-	Pooled OLS is preferred
BankTrans	1.0000	0.9959	-	Pooled OLS is preferred
Mobile	1.0000	0.9871	-	Pooled OLS is preferred
DV: Unemployment				
Startup	0.0000	0.0000	0.7029	REM is preferred
Internet	0.0000	0.0000	0.6547	REM is preferred
BankTrans	0.0000	0.0000	0.9962	REM is preferred
Mobile	0.0000	0.0000	0.7220	REM is preferred
DV: GFCF				
Startup	0.0000	0.0000	0.5500	REM is preferred
Internet	0.0000	0.0000	0.7140	REM is preferred
BankTrans	0.0000	0.0000	0.5886	REM is preferred
Mobile	0.0000	0.0000	0.1133	REM is preferred
DV: CO2				
Startup	0.0000	0.0000	0.0898 (Sargan Hansen Test)	REM is preferred
Internet	0.0000	0.0000	0.9821	REM is preferred
BankTrans	0.0000	0.0000	0.9455	REM is preferred

Mobile	0.0000	0.0000	0.1846 (Sargan Hansen Test)	REM is preferred

For model selection, the results vary across the total and direct effect models based on the Breusch-Pagan Test, Redundant Fixed Effect Test, and Hausman or Sargan-Hansen Test. For the models with HFCE and GDP as the dependent variables, the results consistently indicate that the Pooled OLS model is the preferred estimator. This suggests that neither random effects nor fixed effects are necessary, as the data do not exhibit significant unobserved heterogeneity across countries or over time for these models.

For the total and direct effect models with Unemployment as the dependent variable, the results consistently favor the REM, as the differences between the REM and FEM estimates are not statistically significant. Similarly, for the direct effect models with GFCF and CO2 as dependent variables, the REM is the preferred model.

However, some models show mixed results. For the total effect models with GFCF as the dependent variable, most models favor REM, except for the model where Mobile is the main independent variable, for which FEM is chosen. Similarly, for the total effect models with CO2 as the dependent variable, most models favor REM, except for the model with Startup as the main independent variable, where FEM is selected.

4.5.2 Diagnostic Check Results

To ensure the reliability of the estimated regression results, the detailed results of the diagnostic checks are reported as follows:

4.5.2.1 Unit Root Test

Table 4.23: Summary of Unit Root Test Results of RQ4

Variable	**p-value [inverse chi-squared (110)]**	**Results**
Startup	0.0000	Stationery
Internet	0.0000	Stationery
BankTrans	0.0000	Stationery
Mobile	0.0000	Stationery
INStartup	0.0000	Stationery
INInternet	0.0000	Stationery
INBankTrans	0.0000	Stationery
INMobile	0.0000	Stationery
FDI	0.0000	Stationery

Based on Table 4.23, the result of the Augmented Dickey Fuller Tests shows a similar p-value of 0.0000 for all FinTech development indicators, FDI, and also the interaction term of FinTech development and income level. These results further indicate that the series is stationary and fulfils the regression model assumptions.

4.5.2.2 Multicollinearity

Table 4.24: Summary of the Multicollinearity Test of RQ4

	vif				
Variable	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**

(i) Total Effect					
INStartup	1.18	1.18	1.18	1.18	1.18
Startup	1.15	1.15	1.15	1.15	1.15
Income Level	1.03	1.03	1.03	1.03	1.03
INInternet	3.05	3.05	3.05	3.05	3.05
Internet	2.64	2.64	2.64	2.64	2.64
Income Level	1.74	1.74	1.74	1.74	1.74
INBankTrans	2.42	2.42	2.42	2.42	2.42
BankTrans	2.20	2.20	2.20	2.20	2.20
Income Level	1.27	1.27	1.27	1.27	1.27
INMobile	1.37	1.37	1.37	1.37	1.37
Mobile	1.31	1.31	1.31	1.31	1.31
Income Level	1.30	1.30	1.30	1.30	1.30
(ii) Direct Effect					
INStartup	1.18	1.18	1.18	1.18	1.18
Startup	1.15	1.15	1.15	1.15	1.15
Income Level	1.03	1.03	1.03	1.03	1.03
FDI	1.00	1.00	1.00	1.00	1.00
INInternet	3.06	3.06	3.06	3.06	3.06
Internet	2.64	2.64	2.64	2.64	2.64
Income Level	1.75	1.75	1.75	1.75	1.75
FDI	1.01	1.01	1.01	1.01	1.01
INBankTrans	2.44	2.44	2.44	2.44	2.44
BankTrans	2.23	2.23	2.23	2.23	2.23
Income Level	2.27	2.27	2.27	2.27	2.27
FDI	1.01	1.01	1.01	1.01	1.01

INMobile	1.37	1.37	1.37	1.37	1.37
Mobile	1.31	1.31	1.31	1.31	1.31
Income Level	1.30	1.30	1.30	1.30	1.30
FDI	1.00	1.00	1.00	1.00	1.00

Based on Table 4.24, the VIF values are similar, with only a slight difference in value for both the total effect and direct effect models. This is because both models include the same independent variables, with the only difference being the additional control variable, FDI, in the direct effect model. Notably, the mean-centering approach was applied to all variables in the models that previously exhibited high VIF values, even though some degree of multicollinearity was expected due to the interaction terms. After mean-centering, all independent variables, moderators, and interaction terms have VIF values below 5. Therefore, it can be concluded that the models do not suffer from multicollinearity and satisfy the regression assumptions.

4.5.2.3 Heteroskedasticity

Table 4.25: Summary of Heteroskedasticity results of RQ4

	Breusch–Pagan test		**White's test**		
Dependent Variable	**χ^2(df)**	**p-value**	**χ^2(df)**	**p-value**	**Results**
<u>(i) Total Effect</u>					
DV: HFCE					
Startup	8.26	0.0041	10.74	0.2166	Heteroskedasticity
Internet	8.15	0.0043	16.72	0.0332	Heteroskedasticity
BankTrans	7.20	0.0073	17.70	0.0236	Heteroskedasticity
Mobile	2.58	0.1081	13.36	0.1002	Homoskedasticity
DV: GDP					
Startup	43.36	0.0000	26.65	0.0008	Heteroskedasticity

Internet	62.61	0.0000	34.20	0.0000	Heteroskedasticity
BankTrans	79.72	0.0000	133.31	0.0000	Heteroskedasticity
Mobile	27.07	0.0000	28.32	0.0004	Heteroskedasticity
(ii) Direct Effect					
DV: HFCE					
Startup	5.67	0.0173	12.38	0.4969	Heteroskedasticity
Internet	62.61	0.0000	34.20	0.0000	Heteroskedasticity
BankTrans	3.82	0.0508	20.68	0.0794	Homoskedasticity
Mobile	1.44	0.2295	14.68	0.3281	Homoskedasticity
DV: GDP					
Startup	18.26	0.0000	156.40	0.0000	Heteroskedasticity
Internet	26.45	0.0000	162.34	0.0000	Heteroskedasticity
BankTrans	39.06	0.0000	184.55	0.0000	Heteroskedasticity
Mobile	11.93	0.0000	154.94	0.0000	Heteroskedasticity

Similarly, only the models that were selected to be estimated by the Pooled OLS method have been run through the conventional heteroskedasticity test. Based on Table 4.25, the heteroskedasticity test results vary across the models, but they remain consistent between the total effect and direct effect specifications, except for the model with HFCE as the dependent variable and BankTrans as the main independent variable. In detail, the models with GDP as the dependent variable all suffered from heteroskedasticity issues, with a p-value lower than 0.05 in both tests. For the model with HFCE as the dependent variable, there are consistent results of a heteroskedasticity problem detected for the model that included Startup and Internet as the main independent variables. In contrast, the remaining models with Mobile as the dependent variable have p-values greater than 0.05 from both tests, indicating that these models do not suffer from heteroskedasticity and maintain constant variance. On the contrary, the models with BankTrans as the main independent variable reported mixed results; the total effect model exhibited heteroskedasticity, whereas the direct effect model was free from heteroskedasticity issues. Therefore, all of the models that suffer from heteroskedasticity will be estimated using cluster robust standard errors to ensure reliable inference.

4.5.2.4 Autocorrelation

Table 4.26: Summary of Autocorrelation Results of RQ4

Variable	**F-statistics**	**p-value**	**Results**
(i) Total Effect			
DV: HFCE			
Startup	0.168	0.6833	No Autocorrelation detected
Internet	0.076	0.7844	No Autocorrelation detected
BankTrans	0.266	0.6084	No Autocorrelation detected
Mobile	0.598	0.4426	No Autocorrelation detected
DV: GDP			
Startup	0.659	0.4204	No Autocorrelation detected
Internet	0.751	0.3899	No Autocorrelation detected
BankTrans	0.670	0.4167	No Autocorrelation detected
Mobile	0.767	0.3851	No Autocorrelation detected
DV: Unemployment			
Startup	43.608	0.0000	Autocorrelation detected
Internet	46.480	0.0000	Autocorrelation detected
BankTrans	48.085	0.0000	Autocorrelation detected
Mobile	47.544	0.0000	Autocorrelation detected
DV: GFCF			
Startup	51.555	0.0000	Autocorrelation detected
Internet	49.414	0.0000	Autocorrelation detected

BankTrans	59.568	0.0000	Autocorrelation detected
Mobile	70.138	0.0000	Autocorrelation detected
DV: CO2			
Startup	85.022	0.0000	Autocorrelation detected
Internet	72.081	0.0000	Autocorrelation detected
BankTrans	60.536	0.0000	Autocorrelation detected
Mobile	65.389	0.0000	Autocorrelation detected
(ii) Direct Effect			
DV: HFCE			
Startup	0.001	0.9794	No Autocorrelation detected
Internet	0.012	0.9144	No Autocorrelation detected
BankTrans	0.016	0.8985	No Autocorrelation detected
Mobile	0.210	0.6483	No Autocorrelation detected
DV: GDP			
Startup	0.808	0.3727	No Autocorrelation detected
Internet	0.928	0.3397	No Autocorrelation detected
BankTrans	0.843	0.3626	No Autocorrelation detected
Mobile	0.857	0.3587	No Autocorrelation detected
DV: Unemployment			
Startup	43.640	0.0000	Autocorrelation detected
Internet	46.518	0.0000	Autocorrelation detected
BankTrans	48.159	0.0000	Autocorrelation detected
Mobile	47.522	0.0000	Autocorrelation detected
DV: GFCF			
Startup	51.556	0.0000	Autocorrelation detected
Internet	49.407	0.0000	Autocorrelation detected
BankTrans	59.661	0.0000	Autocorrelation detected

Mobile	70.121	0.0000	Autocorrelation detected
DV: CO2			
Startup	85.048	0.0000	Autocorrelation detected
Internet	72.134	0.0000	Autocorrelation detected
BankTrans	60.545	0.0000	Autocorrelation detected
Mobile	65.362	0.0000	Autocorrelation detected

Based on Table 4.26, the Wooldridge test reports different outcomes across models depending on which economic performance variable is used as the dependent variable. However, for each dependent variable, the total effect model and the direct effect model show the same conclusion regarding the presence or absence of autocorrelation. For the models, with HFCE and GDP as the dependent variables, there is no autocorrelation detected, as the p-values are greater than 0.05. In contrast, the remaining models all report p-values below the 0.05 threshold, indicating the presence of autocorrelation. This suggests that these models violate the assumption of error-term independence and therefore require the use of cluster-robust standard errors to ensure reliable inference.

In short, based on all diagnostic test results, for models exhibiting heteroskedasticity, autocorrelation, or both, cluster-robust standard errors will be applied to ensure reliable estimation by accounting for non-constant variance. In contrast, the total effects model with Mobile as the main independent variable, and the direct effects models with BankTrans and Mobile as the main independent variables, satisfy all regression assumptions. Therefore, a standard Pooled OLS method can be applied without any adjustments to the dataset.

4.5.3 Regression Analysis

For Research Question 4, the model analysis is organized by the main independent variables: Startup, Internet, BankTrans, and Mobile. The detailed regression results are analysed in detail as follows.

4.5.3.1 FinTech Startup

Table 4.27: Regression Results of Total Effect Models for RQ4 - FinTech Startup

	Dependent Variable				
Statistics	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**
Adjusted R-Squared	0.0239	0.0098	0.0173	0.0072	0.0500
F-statistic (p-value)	6.41 0.0009	2.47 0.0720	16.07 0.0011	2.48 0.4794	1.70 0.1915
Startup					
Coefficient	-0.0094	-0.0100	0.0435***	-0.0073	-0.0874
t-statistic	-0.74	-1.10	3.82	-0.37	-0.41
(p-value)	0.465	0.277	0.000	0.711	0.684
Income Level					
Coefficient	-0.9876***	-0.6043*	-1.1703	-0.2065	omitted
t-statistic	-2.98	-1.89	-1.42	-0.23	
(p-value)	0.004	0.063	0.155	0.821	
INStartup					
Coefficient	-0.0346	-0.0122	-0.0119	-0.0307	0.6492
t-statistic	-1.64	-0.68	-0.60	-0.97	1.64
(p-value)	0.107	0.499	0.549	0.334	0.106
Constant					
Coefficient	2.8538	2.7603	7.5126	22.4111	141.5136
t-statistic	12.51	14.25	12.02	34.42	166.52
(p-value)	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.27, the regression results reported that the majority of the startups are not statistically significant to the variation of the economic performance, which included HFCE, GDP, GFCF and CO2, except for the model with Unemployment as the dependent variable.

For the model with HFCE as the dependent variable, the adjusted R-squared is 0.0236, indicating that only 2.36% of the variation in HFCE is explained by the Startup, income level and INStartup. Although the adjusted R-squared is low, the F-statistic indicates that the model is statistically significant with a p-value of 0.0009 at the 1% significance level. In the model, the income level is highly significant to the variation of the HFCE, indicating that for a one-level increase in the income level, the HFCE will decrease by 0.9876. It further implies that the relationship between income level and HFCE is reversed. In contrast, the other variables are reported as not statistically significant, where the effect is not meaningful to the variation of HFCE.

Furthermore, for the second model, with GDP as the dependent variable, the explanatory power of the model is extremely low, where only 0.98% of the variation of GDP growth is explained by this model. In this model, only the income level is marginally significant in explaining the variation of GDP with a negative coefficient. These results suggest that the countries with higher income levels tend to have slower GDP growth, but there is no sufficient evidence to prove that effect, as the p-value is greater than 0.05. For the variables, FDI and INFDI, both have negative coefficients, but are not statistically significant in affecting the variation of GDP. Overall, this model is not statistically significant according to the F-statistic, which has a p-value of 0.0720.

The model with Unemployment as the dependent variable also has a low explanatory power, where only 1.73% of the variation of the unemployment rate is explained by the Startup. However, the overall model is still highly significant (p=0.0011). Focusing on the individual effect, the effect of the startup is highly significant on the variation of the unemployment rate at the average level. The coefficient (β = 0.0435) further indicates that by a unit increase in the number of startups, the unemployment rate will increase by 0.0435, suggesting a positive effect. In contrast, none of the income levels and the interaction term is statistically significant. Therefore, it can be concluded that the relationship between Startup and Unemployment is not moderated by income level.

Similar to the other models, the models with GFCF and CO_2 as the dependent variables have low explanatory power, with R-squared values of 0.0072 and 0.0500, respectively. In more detail, none of the variables are statistically significant in these models. These results further indicate that there is no evidence to conclude that Startup has any effect on GFCF or CO_2. Notably, in the fixed effect model with CO_2 as the dependent variable, income level is omitted due to its time-invariant nature, as it does not vary over time within individual countries.

Table 4.28: Regression Results of Direct Effect Models for RQ4 - FinTech Startup

	Dependent Variable					
Statistics	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**
Adjusted R-Squared	0.0307	0.0174	0.0178	0.0067	0.0047
F-statistic (p-value)	6.18 0.0004	5.73 0.0006	87.50 0.0000	2.56 0.6330	7.71 0.1030
Startup Coefficient	-0.0095	-0.0101	0.0434***	-0.0075	-0.0637

t-statistic	-0.74	-1.11	3.80	-0.38	-0.30
(p-value)	0.462	0.272	0.000	0.707	0.768
Income Level					
Coefficient	-0.9977***	-0.6152*	-1.1733	-0.2089	41.3924
t-statistic	-3.03	-1.96	-1.42	-0.23	1.01
(p-value)	0.004	0.056	0.155	0.819	0.768
INStartup					
Coefficient	-0.0346	-0.0122	-0.0124	-0.0311	0.6200
t-statistic	-1.64	-0.68	-0.62	-0.98	1.56
(p-value)	0.106	0.498	0.533	0.328	0.120
FDI					
Coefficient	0.0096**	0.0104***	0.0013***	0.0009	-0.0001
t-statistic	2.17	4.01	6.42	0.33	-0.08
(p-value)	0.034	0.000	0.000	0.739	0.940
Constant					
Coefficient	2.8224	2.7264	7.5092	22.4091	141.5768
t-statistic	12.45	14.58	12.00	34.39	3.56
(p-value)	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.28, there are regression results that present the direct effect of the Startup on the economic performance with the mediator, FDI. The overall results are considered similar to the total effect models, with the majority of the models having extremely low explanatory power. Among all the direct effect models, the mediator FDI is only significant in the models with HFCE, GDP, and Unemployment as the dependent variables, indicating that only these models have the potential for a mediating effect of FDI. However, the results in Section 4.3 show that Startups do not have a significant effect on FDI. Therefore, FDI cannot serve as a mediator in this relationship, even though Startups have a statistically significant effect on Unemployment.

Overall, it can be concluded that FDI does not mediate the relationship between FinTech startups and any of the economic performance indicators. Combining the results of the total and direct effect models, the effect of startups is only significant for the unemployment rate, and this effect is positive. Therefore, the overall results contradict the hypotheses that were outlined.

4.5.3.2 Internet

Table 4.29: Regression Results of Total Effect Models for RQ4 - Internet

	Dependent Variable				
Statistics	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**
Adjusted R-Squared	0.0216	0.0094	0.0208	0.0034	0.0141
F-statistic (p-value)	3.81 0.0150	1.35 0.2684	5.62 0.1316	1.85 0.6041	8.53 0.0362
Internet Coefficient t-statistic (p-value)	 -0.0039 -0.20 0.840	 -0.0095 -0.68 0.498	 -0.0308 -1.50 0.133	 0.0085 0.27 0.791	 0.3559 0.82 0.415
Income Level Coefficient t-statistic (p-value)	 -1.0328* -1.99 0.051	 -0.3193 -0.70 0.486	 -1.1109 -1.16 0.247	 0.4491 0.40 0.688	 30.3485 0.72 0.473
INInternet Coefficient t-statistic (p-value)	 -0.0160 -1.11 0.270	 0.0056 0.43 0.666	 -0.0490** -2.14 0.032	 0.0474 1.21 0.228	 -0.0852 -0.16 0.874
Constant Coefficient t-statistic	 2.9696 10.81	 2.6672 11.00	 8.0702 10.65	 21.7812 24.18	 143.9244 4.12

(p-value)	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.29, the regression results indicate that models with the Internet as the main independent variable have very low explanatory power for economic performance. In addition, most of the individual effects are not statistically significant, suggesting that Internet penetration alone has limited explanatory value.

In detail, the first model, with HFCE as the dependent variable, has an R-squared of 0.0216, indicating that only 2.16% of the variation is explained by the model. The F-statistic of the model indicates the overall model is still significant with a p-value of 0.0150, implying that at least one variable contributes meaningfully to the model. Within this model, only income level is marginally significant at the 10% level. The negative coefficients of the income level indicate that as the increase of level of income increases, the HFCE will decrease by 1.0328 at the average level. For other FDI and INFDI, both have negative coefficients but are not statistically significant. Therefore, it can be concluded that the Internet does not have a meaningful effect on HFCE, and no moderating effect is observed in this model.

In the second model, with Unemployment as the dependent variable, the explanatory power is similarly low, with an R-squared of 0.0208. The F-statistic indicates that the overall model is not statistically significant. Both main independent variables, Internet and income level, are also not statistically significant ($p > 0.05$). However, the interaction term between Internet and income level is statistically significant, with a negative coefficient ($\beta = -0.0490$) at the average level. This indicates that the effect of the Internet on Unemployment is conditional on income level. Specifically, Income level weakens the effect of Internet on Unemployment, as supported by the significance of the moderator.

On the contrary, for the remaining models with GDP, GFCF, and CO2 as the dependent variables, the explanatory power is very low, with only around 1% or less of the variation in the dependent variables explained by the models. Collectively, these models are not statistically significant, except for the model with CO2 as the dependent variable, which has a p-value of 0.0362. In detail, for all the models considered, none of the independent variables, which include Internet, income level, and INInternet, are statistically significant. Therefore, based on the results presented in Table 4.29, it can be concluded that the Internet has no meaningful effect on GDP, GFCF, or CO2. Furthermore, as the interaction terms are not statistically significant, there is no evidence of a moderating effect of income level on the relationship between Internet and GDP, GFCF, or CO2.

Table 4.30: Regression Results of Direct Effect Models for RQ4 - Internet

	Dependent Variable				
Statistics	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**
Adjusted R-Squared	0.0281	0.0170	0.0213	0.0036	0.0141
F-statistic (p-value)	3.57 0.0118	5.31 0.0011	20.89 0.0003	1.87 0.7589	12.33 0.0150
Internet Coefficient t-statistic (p-value)	 -0.0017 -0.09 0.929	 -0.0071 -0.51 0.612	 -0.0304 -1.48 0.139	 0.0089 0.28 0.783	 0.3575 0.82 0.415
Income Level Coefficient t-statistic (p-value)	 -1.0648** -2.06 0.044	 -0.3547 -0.79 0.435	 -1.1134 -1.16 0.246	 0.4480 0.40 0.689	 30.3429 0.72 0.474
INInternet					

Coefficient	-0.0146	0.0071	-0.0486**	0.0479	-0.0833
t-statistic	-1.04	0.56	-2.12	1.21	-0.15
(p-value)	0.305	0.575	0.034	0.226	0.878
FDI					
Coefficient	0.0094*	0.0103***	0.0011***	0.0010	0.0039
t-statistic	1.98	3.90	2.63	0.40	0.96
(p-value)	0.053	0.000	0.009	0.689	0.336
Constant					
Coefficient	2.9229	2.6157	8.0612	21.7723	143.8882
t-statistic	10.67	10.96	10.62	24.06	4.11
(p-value)	0.000	0.00	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

For the direct effect models, the overall results are considered similar to the total effect model, even after including the mediator, FDI. The explanatory power of the models remains low, and the significance levels of the variables remain unchanged in both the total-effect and direct-effect models. Additionally, FDI, individually only significant in the models with HFCE, GDP and Unemployment as the dependent variable. However, Internet does not have a statistically significant effect on FDI, and as the main independent variable, it also shows no significant effect on any of the macroeconomic performance indicators. Therefore, there is no potential for the mediating effect of FDI between the Internet and the macroeconomic performance

In short, the regression results of both the total and direct effect models indicate that the Internet has no significant effect on any of the macroeconomic performance indicators tested in this research. At the same time, FDI also shows no mediating effect on the relationship between the Internet and macroeconomic performance. This suggests that the effect of the Internet is not significant, neither directly nor indirectly.

4.5.3.3 BankTrans

Table 4.31: Regression Results of Total Effect Models for RQ4 - BankTrans

	Dependent Variable				
Statistics	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**
Adjusted R-Squared	0.0192	0.0084	0.0905	0.0560	0.0186
F-statistic	3.36	1.04	12.62	2.39	6.48
(p-value)	0.0253	0.3807	0.0055	0.4957	0.0904
BankTrans					
Coefficient	0.0302	0.0149	-0.3877**	0.2757	1.8577
t-statistic	0.41	0.22	-2.19	1.53	0.50
(p-value)	0.682	0.829	0.028	0.127	0.619
Income Level					
Coefficient	-0.8709**	-0.5638	-1.1046	-0.1766	30.1929
t-statistic	-2.04	-1.59	-1.33	-0.18	0.69
(p-value)	0.046	0.118	0.184	0.857	0.488
INBankTrans					
Coefficient	0.0360	0.0334	-0.5746***	0.2884	-3.2989
t-statistic	0.43	00.47	-3.39	1.33	-0.55
(p-value)	0.672	0.640	0.001	0.184	0.581
Constant					
Coefficient	2.7386	2.6962	8.1388	22.0178	146.6528
t-statistic	9.94	12.54	11.90	29.27	4.12
(p-value)	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.31, the results primarily present the regression analysis of BankTrans as the main independent variable, including its moderating effects on economic performance. Overall, the adjusted R-squared values across all five models are relatively low, suggesting that the main independent variable, BankTrans, explains only a small proportion of the variation in economic performance indicators. The regression results also vary across the models with mixed coefficient signs and inconsistent significance levels.

For the first model, with HFCE as the dependent variable, the R-squared is 0.0192, indicating that only 1.92% of HFCE's variation is explained by this model. Although the model's explanatory power is extremely low, the F statistic indicates that the overall model remains statistically significant. Focusing on the individual effects, only the variable income level is statistically significant at the 5% level in this model. In detail, the coefficient of Income Level (β = -0.8709) indicates that the higher income level is associated with lower HFCE, suggesting a negative relationship. For the BankTrans and INBankTrans, both suggest a positive relationship with the HFCE; however, the effect is not statistically significant.

Similarly, the model with Unemployment as the dependent variable has a highly significant effect but low explanatory power, where only 9.05% of the variation of Unemployment is explained by the model. In this model, the variable BnakTrans is statistically significant for the variation of Unemployment. The negative coefficient further suggests that a 1% increase in BankTrans, the unemployment rate will decrease by 0.3877. Meanwhile, the interaction term, INBankTrans, is highly significant with a p-value of 0.001, further supporting the moderating effects. The coefficient of the interaction term (β = -0.5746) indicates that the negative effect of the BankTrans decreases as the income levels increase, implying that the effect is stronger for lower-income countries. However, the income level individually does not have a significant effect on the unemployment rate.

On the contrary, in the other models with GDP, GFCF, and CO2 as dependent variables, none of the variables are significant, either individually or jointly. The lack of meaningful results in these models is further supported by their low explanatory power, with only 5% or even less of the variation in the dependent variables explained. Therefore, it can be concluded that BankTrans has no significant effect on GDP, GFCF and CO2, either individually or through moderating effects.

Table 4.32: Regression Results of Direct Effect Models for RQ4 - BankTrans

	Dependent Variable				
Statistics	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**
Adjusted R-Squared	0.0264	0.0164	0.0905	0.0574	0.0186
F-statistic (p-value)	2.57 0.0375	4.80 0.0022	21.40 0.0003	2.60 0.6270	8.55 0.733
BankTrans					
Coefficient	0.0496	0.0357	-0.3851**	0.2842	1.8651
t-statistic	0.40	0.58	-2.15	1.55	0.49
(p-value)	0.692	0.565	0.031	0.121	0.624
Income Level					
Coefficient	-0.8861**	-0.5801*	-1.1045	-0.1781	30.1965
t-statistic	-2.46	-1.69	-1.33	-0.18	0.69
(p-value)	0.014	0.097	0.185	0.856	0.489
INBankTrans					
Coefficient	0.0569	0.0558	-0.5711***	0.2990	-3.2863
t-statistic	0.48	0.8	-3.31	1.36	-0.54
(p-value)	0.629	0.411	0.001	0.175	0.589
FDI					
Coefficient	0.0099*	0.0106***	0.0004	0.0015	0.0012
t-statistic	1.68	3.88	0.63	0.61	0.13
(p-value)	0.095	0.000	0.532	0.540	0.900
Constant					
Coefficient	2.6824	2.6359	8.1335	22.001	146.6345
t-statistic	9.36	13.05	11.83	29.09	4.12
(p-value)	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

In the direct effect models, the regression results are highly similar to the total effect model, with overall low explanatory power. Based on Table 4.32, FDI, individually, only has a statistically significant effect in the model with HFCE and GDP as the dependent variables. Therefore, only these models will be compared with the total-effect models to further assess the presence of any mediating effects. However, in these models, the main independent variable, BankTrans, has no statistically significant effects on specific macroeconomic performance. In addition, the results in Section 4.3 have shown that BankTrans has no statistically significant effect on FDI. Therefore, there is no potential mediating effect of FDI on the relationship between the Internet and economic performance.

In summary, neither the significance levels nor the coefficients of BankTrans, the FinTech development indicator, changed after the inclusion of FDI as a mediator in the direct-effect models. Therefore, it can be confirmed that there is no mediating effect of FDI in the relationship between BankTrans and economic performance. Overall, the impact of FinTech development through BankTrans is limited, with only a negative and significant effect observed on the unemployment rate.

4.5.3.4 Mobile

Table 4.33: Regression Results of Total Effect Models for RQ4 - Mobile

	Dependent Variable				
Statistics	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**
Adjusted R-Squared	0.0266	0.0131	0.0214	0.0001	0.0149
F-statistic	3.47	2.74	4.32	1.73	1.39

(p-value)	0.0164	0.0520	0.2286	0.1875	0.7085
Mobile					
Coefficient	0.02054	0.0181*	-0.0234	0.0319	0.1020
t-statistic	1.60	1.96	-1.38	1.17	0.20
(p-value)	0.110	0.056	0.167	0.247	0.845
Income					
Level	-1.1073***	-0.6927**	-0.8946	Omitted	37.8811
Coefficient	-3.04	-2.07	-1.07		0.90
t-statistic	0.003	0.043	0.283		0.367
(p-value)					
INMobile					
Coefficient	-0.0014	0.0080	-0.0162	-0.0754	0.0479
t-statistic	-0.10	0.56	-1.1	-1.60	0.08
(p-value)	0.924	0.580	0.251	0.115	0.934
Constant					
Coefficient	2.7887	2.6805	7.5963	22.8541	142.5872
t-statistic	10.35	12.98	11.90	71.84	3.86
(p-value)	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.33, the regression results examining the relationship between Mobile and economic performance show that the overall relationship is weak. Across all five models, the explanatory power is relatively low, indicating that Mobile has limited capacity to explain variations in economic performance.

For the first model, where HFCE is the dependent variable, the R-squared value is only 0.0266, meaning that 2.66% of the variation in HFCE is explained by the model. In this specification, income level is the only statistically significant variable ($p = 0.003$). The negative coefficient of income level ($\beta = -1.1073$) indicates that higher income levels are associated with lower HFCE. However, Mobile and its interaction term (INMobile) are both statistically insignificant, suggesting that Mobile has no meaningful direct or moderating effect on HFCE.

Similarly, in the model with GDP as the dependent variable, the explanatory power remains low, with only 1.31% of GDP variation explained. Mobile is marginally significant with a positive coefficient (β = 0.0181), indicating that a one-unit increase in Mobile penetration is associated with a 0.0181 increase in GDP growth. However, the effect is weak and only significant at the 10% level, providing limited evidence of a meaningful relationship. Income level is statistically significant at the 5% level, with a negative coefficient (β = –0.6927), showing that higher income levels are associated with lower GDP growth. The interaction term is not significant, indicating no moderating effect of income level on the Mobile–GDP relationship.

In contrast, the remaining models with Unemployment, GFCF, and CO2 as dependent variables also exhibit low explanatory power and are not statistically significant ($p > 0.05$). Additionally, none of the variables in these models are significant. These results collectively indicate that Mobile has no meaningful effect on Unemployment, GFCF, or CO2. It further suggests that other structural variables might play a more important role than Mobile in explaining these economic performances.

Table 4.34: Regression Results of Direct Effect Models for RQ4 - Mobile

	Dependent Variable				
Statistics	**HFCE**	**GDP**	**Unemployment**	**GFCF**	**CO2**
Adjusted R-Squared	0.0332	0.0205	0.0222	0.0001	0.0150
F-statistic (p-value)	3.27 0.0119	5.64 0.0007	63.08 0.0000	3.60 0.4622	3.34 0.5024
Mobile Coefficient	0.0203	0.0178*	-0.2300	0.0282	0.1028

t-statistic	1.59	1.99	-1.36	1.33	0.20
(p-value)	0.114	0.052	0.175	0.184	0.845
Income					
Level	-1.1161***	-0.7022**	-0.8946	-1.0182	37.8839
Coefficient	-3.07	-2.13	-1.07	-1.04	0.90
t-statistic	0.002	0.037	0.283	0.300	0.367
(p-value)					
INMobile					
Coefficient	-0.0015	0.0078	-0.0157	-0.0545	0.0492
t-statistic	-0.10	0.56	-1.11	-1.49	0.08
(p-value)	0.917	0.580	0.266	0.135	0.932
FDI					
Coefficient	0.0095	0.0102***	0.0013***	0.0006	0.0028
t-statistic	1.62	4.28	5.23	0.23	0.39
(p-value)	0.106	0.000	0.000	0.817	0.699
Constant					
Coefficient	2.7584	2.6477	7.5888	22.711	142.5692
t-statistic	10.23	13.03	11.88	33.35	3.86
(p-value)	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.34, the regression results of the direct-effect models remain largely similar to the total-effect models, even after including FDI as the mediator. Specifically, the explanatory power of all models remains low, and the significance levels of the variables do not change across the five specifications. At the same time, the mediator FDI is statistically significant only in the models with GDP and Unemployment as the dependent variables. Therefore, only these two models present the potential for examining mediating effects. However, the main independent variable, Mobile, has no statistically significant effect on FDI and any of the economic performance indicators. As a result, there is no potential for a mediating effect between Mobile and economic performance.

In summary, the inclusion of the mediator, FDI, does not reduce or alter its effect on FinTech development, which includes Startup, Internet, BankTrans, and Mobile, further indicating the absence of any mediating relationship. Focusing on the relationship, the analysis has revealed that FinTech development has a limited direct impact on macroeconomic performance and highly depends on the type of FinTech. Specifically, only the effect of BankTrans on unemployment aligns with the hypothesis, consistent with Endogenous Growth Theory and the findings of Choudhary et al. (2025). While the effect of Startup is significant, it has a positive impact on the unemployment rate, contradicting the hypothesis. In this study, the insignificant effects of FinTech development on economic performance are consistent with the Too Much Finance Hypothesis and the studies of Liu & Chu (2024) and Ochirova & Miriakov (2025), but largely contradict the findings of Jafri et al. (2025), Mashamba et al. (2023), Salleh et al. (2025), and Sayari et al. (2025).

4.6 Research Question 5

For Research Question 5, the analysis is similar to RQ3, with the dependent variable changed to SDGs outcomes, which are SDGIndex, SDG1, SDG8, SDG9, SDG10, and SDG13. Accordingly, the interaction term of FDI with income level is included to assess the effect of FDI on SDGs while accounting for the moderating role of income level. In addition, a similar mean-centering approach is applied to all independent variables to ensure that the model reflects real-world conditions by interpreting the effects at the average level of the data.

4.6.1 Model Selection

Table 4.35: Summary of Model Selection Tests Results of RQ5

	Breusch-Pagan LM Test	**Redundant Fixed Effects Test**	**Hausman Test**	
Variable	**p-value**	**p-value**	**p-value**	**Results**
SDG Index	0.0000	0.0000	0.9647	REM is preferred
SDG 1	0.0000	0.0000	0.0046 (Sargan Hansen Test)	FEM is preferred
SDG 8	0.0000	0.0000	0.7910	REM is preferred
SDG 9	0.0000	0.0000	0.7635	REM is preferred
SDG 10	0.0000	0.0000	0.855	REM is preferred

SDG 13	0.0000	0.0000	0.0473 (Sargan Hansen Test)	FEM is preferred

Based on Table 4.35, the results of the model selection of the Breusch-Pagan test and the Redundant Fixed Effect test are consistent across all models, with the p-values of 0.0000, indicating that Pooled OLS is insufficient compared to the REM and FEM due to the presence of unobserved heterogeneity across panels. Therefore, the additional Hausman test is required to choose between REM and FEM. Based on the results, the p-values reported in the tests for the models with SDG Index, SDG 8, SDG 9, and SDG 10 as the dependent variables are all greater than 0.05, indicating that the REM is more suitable than the FEM due to the lack of significant correlation between the individual effects and the regressors. In contrast, for the model with SDG 1 and SDG 13 as the dependent variables, the Hausman test result indicates that the FEM is more appropriate, suggesting that unobserved country-specific characteristics are correlated with the explanatory variables and therefore need to be controlled for.

4.6.2 Diagnostic Check Results

4.6.2.1 Unit Root Test

Table 4.36: Summary of Unit Root Test Results of RQ5

Variable	p-value [inverse chi-squared (110)]	Results
FDI	0.0000	Stationery
INFDI	0.0000	Stationery

Similar to the RQ3, the p-value of the same independent variable, FDI, in the Augmented Dickey-Fuller test is reported as 0.0000, indicating that the series is stationary. These results indicate that the models have fulfilled one of the requirements of regression estimation.

4.6.2.2 Multicollinearity

Table 4.37: Summary of the Multicollinearity Test of RQ5

	VIF					
Variable	**SDG Index**	**SDG 1**	**SDG 8**	**SDG9**	**SDG 10**	**SDG 13**
INFDI	41.85	41.85	41.85	41.85	41.85	41.85
FDI	41.85	41.85	41.85	41.85	41.85	41.85
Income Level	1.07	1.07	1.07	1.07	1.07	1.07

Similar to Section 4.4.2.2, as the independent variables are the same across the six models, therefore, the VIF values remain the same as presented in Table 4.37. In addition, these independent variables are identical to those used in the models discussed in Section 4.4. The VIF values for INFDI and FDI exceed 5, with both reaching 41.85, indicating the presence of multicollinearity. However, this is expected because the interaction term INFDI is constructed directly from its component variables and is therefore naturally correlated with FDI. As a result, the high VIF values do not indicate a substantive issue and can be reasonably ignored in this context.

4.6.2.3 Heteroskedasticity

As discussed in Section 4.6.1, the preferred models are REM and FEM, meaning that Pooled OLS is not suitable. Standard heteroskedasticity tests, such as the Breusch-Pagan or White tests, are therefore not directly applicable to REM and FEM. However, the use of REM and FEM still suggests the presence of potential heteroskedasticity and/or within-cluster correlation. To address this, cluster-robust standard errors are applied to all models, ensuring that hypothesis tests and confidence intervals remain valid. As a result, the reliability and robustness of the estimated coefficients are improved, providing more trustworthy inference.

4.6.2.4 Autocorrelation

Table 4.38: Summary of Autocorrelation Results of RQ5

Dependent Variable	**F-statistics**	**p-value**	**Results**
SDG Index	129.684	0.0000	Autocorrelation detected
SDG 1	10.447	0.0021	Autocorrelation detected
SDG 8	127.186	0.0000	Autocorrelation detected
SDG 9	128.882	0.0000	Autocorrelation detected
SDG 10	23.4233	0.0000	Autocorrelation detected
SDG 13	23.521	0.0000	Autocorrelation detected

For the autocorrelation test, Table 4.38 shows consistent results, with p-values less than 0.05 across all models in the Wooldridge Test, indicating the presence of autocorrelation. Based on these results, the assumption of no autocorrelation is violated for all models. Therefore, a similar approach, cluster-robust standard errors, is applied to ensure that the coefficient estimates remain unbiased and the inference is reliable.

In summary, based on all diagnostic checks, the models are subject to both autocorrelation and potential heteroskedasticity. Therefore, cluster-robust standard errors are applied to all models. This adjustment corrects the standard errors for within-cluster correlation and heteroskedasticity, enhancing the reliability and validity of the estimated results.

4.6.3 Regression Analysis

Table 4.39: Regression Results of RQ5

	Dependent Variable					
Statistics	**SDG Index**	**SDG 1**	**SDG 8**	**SDG 9**	**SDG 10**	**SDG 13**
Adjusted R-Squared	0.6466	0.1563	0.2934	0.5850	0.1895	0.0060
F-statistic (p-value)	101.72 0.0000	2.48 0.0935	22.57 0.0000	78.88 0.0000	17.52 0.0006	0.66 0.5196
FDI						
Coefficient	-0.0080 **	0.02718 *	-0.0002	-0.0247	0.0006	-0.0068
t-statistic (p-value)	-2.02 0.043	1.73 0.089	-0.02 0.983	-1.03 0.303	0.09 0.930	-1.03 0.308
Income Level						
Coefficient	7.8242 ***	Omitted	4.6305 ***	21.7128 ***	15.7361 ***	omitted
t-statistic (p-value)	9.01 0.000		3.70 0.000	8.61 0.000	3.76 0.000	
INFDI						
Coefficient	0.0111 *	-0.0402 *	-0.0022	0.0360	-0.0020	0.0069
t-statistic (p-value)	1.88 0.060	-1.72 0.091	-0.13 0.896	1.03 0.302	-0.19 0.852	0.72 0.475

Constant						
Coefficient	73.7813	88.6402	73.8438	60.7677	67.0829	83.2702
t-statistic	120.06	5747.37	98.06	31.60	19.31	1.30
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.39, the regression results examining the relationship between FDI and SDG achievement vary across models, with some areas showing high significance while others do not. This variation reflects differences in the relationships and significance levels between FDI, the composite SDG Index, and individual SDGs. Overall, the models exhibit moderate explanatory power, except for the model with SDG 13 as the dependent variable, which shows lower explanatory power.

In the first model, with the composite SDG Index as the dependent variable, the explanatory power is high, with 64.66% of the variation in SDG achievement explained by the model. The F-statistic is highly significant ($p = 0.000$), indicating that the model is significant at the 1% level. Focusing on individual effects, the main variable, FDI, is statistically significant at the 4% level with a negative coefficient ($\beta = -0.0080$), suggesting that a one-unit increase in FDI is associated with a 0.0080 decrease in the composite SDG Index, indicating a negative relationship. Meanwhile, Income level is also highly significant ($p = 0.000$), with a positive coefficient, indicating that higher income levels are associated with higher SDG achievement. The interaction term, INFDI, is marginally significant at the 10% level, with a coefficient suggesting that the negative effect of FDI slightly increases as income level rises. However, it is notable that there is no strong evidence to support a meaningful moderating effect of income level in this model.

Furthermore, in the model with SDG 1 as the dependent variable, the explanatory power is 15.63%, and the results are only marginally significant at the 10% level. Notably, in this FEM, income level is omitted because it is a categorical variable that is time-invariant. Focusing on the individual effect, FDI has a positive coefficient ($\beta = 0.0272$), indicating that an increase in FDI contributes to a 0.0272 increase in the SDG 1 score. The negative coefficient of INFDI further suggests that the positive effect of FDI on SDG 1 decreases as income level increases. However, both the direct effect and the moderating effect are only marginally significant at the 10% level, providing no strong evidence to support a definitive relationship.

On the contrary, for the remaining models with SDG 8, 9, 10, and 13 as the dependent variables, the FDI has no statistically significant effect on these models, neither as an individual effect nor as a moderating effect. The p-values of both FDI and INFDI exceed 0.05 in all of these models, indicating no evidence to support a meaningful relationship. However, it is notable that the income level variable is highly significant in all models with a positive coefficient. This finding indicates that higher-income countries tend to achieve higher SDG scores, both in the composite SDG index and in the individual SDG dimensions.

In summary, FDI alone does not significantly impact or advance SDG achievements. Its effects show potential benefits for poverty reduction but are limited regarding economic growth, inequality, infrastructure, or climate action, which are the areas of the SDGs tested in this study. Therefore, the overall results contradict the hypotheses outlined. Although the overall results are not statistically significant, they are consistent with the Absorptive Capacity Theory, which suggests that the effect of FDI is highly conditional and context dependent. Past studies by Alvarado et al. (2017) and Rodríguez-Chávez et al. (2024) further support the insignificant effect of FDI. In contrast, these findings contradict the FDI-Growth Spillover Theory and the studies of Al-Smadi & Al-Smadi (2024) and Mashamba et al. (2023), which argue that FDI is often linked to advancements, particularly in economic dimensions.

4.7 Research Question 6

For Research Question 6, which is more focused on examining the mediating effect of FDI in the relationship between FinTech development and the achievement of SDGs. Similar to Research Question 3, three models will be constructed for each SDG, with the interaction term of Fintech development and income level. In addition, it is important to note that the total effect of FDI has already been discussed in Section 4.6. Therefore, in this section, only the diagnostic checks and regression analyses of the total effect of FinTech development and the direct effect of FDI on SDGs will be presented. Similarly, the mean-centering is also applied to all of the models with interaction terms.

4.7.1 Model Selection

Table 4.40: Summary of Model Selection Tests Results of RQ6

	Breusch-Pagan LM Test	**Redundant Fixed Effects Test**	**Hausman Test**	
Variable	**p-value**	**p-value**	**p-value**	**Results**
(i) Total Effect				
DV: SDG Index				
Startup	0.0000	0.0000	0.1104	REM is preferred
Internet	0.0000	0.0000	0.1755	REM is preferred
BankTrans	0.0000	0.0000	0.1416	REM is preferred
Mobile	0.0000	0.0000	0.0005	FEM is preferred
DV: SDG 1				
Startup	0.0000	0.0000	0.0133	FEM is preferred

Internet	0.0000	0.0000	0.0000 (Sargan Hansen Test)	FEM is preferred
BankTrans	0.0000	0.0000	0.7214	REM is preferred
Mobile	0.0000	0.0000	0.0000	FEM is preferred
DV: SDG 8				
Startup	0.0000	0.0000	0.3720	REM is preferred
Internet	0.0000	0.0000	0.3177	REM is preferred
BankTrans	0.0000	0.0000	0.4247	REM is preferred
Mobile	0.0000	0.0000	0.1536	REM is preferred
DV: SDG 9				
Startup	0.0000	0.0000	0.000 (Sargan Hansen Test)	FEM is preferred
Internet	0.0000	0.0000	0.0000 (Sargan Hansen Test)	FEM is preferred
BankTrans	0.0000	0.0000	0.0876	REM is preferred
Mobile	0.0000	0.0000	0.2837	REM is preferred
DV: SDG 10				
Startup	0.0000	0.0000	0.0150	FEM is preferred
Internet	0.0000	0.0000	0.0370	FEM is preferred
BankTrans	0.0000	0.0000	0.0642	REM is preferred
Mobile	0.0000	0.0000	0.1411	REM is preferred
DV: SDG 13				
Startup	0.0000	0.0000	0.5552	REM is preferred

Internet	0.0000	0.0000	0.0054 (Sargan Hansen Test)	FEM is preferred
BankTrans	0.0000	0.0000	0.3526	REM is preferred
Mobile	0.0000	0.0000	0.6916	REM is preferred
<u>(ii) Direct Effect</u>				
DV: SDG Index				
Startup	0.0000	0.0000	0.2992	REM is preferred
Internet	0.0000	0.0000	0.8679	REM is preferred
BankTrans	0.0000	0.0000	0.2999	REM is preferred
Mobile	0.0000	0.0000	0.0042	FEM is preferred
DV: SDG 1				
Startup	0.0000	0.0000	0.1075	REM is preferred
Internet	0.0000	0.0000	0.0000 (Sargan Hansen Test)	FEM is preferred
BankTrans	0.0000	0.0000	0.8945	REM is preferred
Mobile	0.0000	0.0000	0.0000	FEM is preferred
DV: SDG 8				
Startup	0.0000	0.0000	0.4403	REM is preferred
Internet	0.0000	0.0000	0.4446	REM is preferred
BankTrans	0.0000	0.0000	0.6121	REM is preferred
Mobile	0.0000	0.0000	0.3517	REM is preferred
DV: SDG 9				

Startup	0.0000	0.0000	0.0001 (Sargan Hansen Test)	FEM is preferred
Internet	0.0000	0.0000	0.0000 (Sargan Hansen Test)	FEM is preferred
BankTrans	0.0000	0.0000	0.2056	REM is preferred
Mobile	0.0000	0.0000	0.3517	REM is preferred
DV: SDG 10				
Startup	0.0000	0.0000	0.1013	REM is preferred
Internet	0.0000	0.0000	0.3521	REM is preferred
BankTrans	0.0000	0.0000	0.1579	REM is preferred
Mobile	0.0000	0.0000	0.3533	REM is preferred
DV: SDG 13				
Startup	0.0000	0.0000	0.6337	REM is preferred
Internet	0.0000	0.0000	0.0118 (Sargan Hansen Test)	FEM is preferred
BankTrans	0.0000	0.0000	0.5156	REM is preferred
Mobile	0.0000	0.0000	0.7038	REM is preferred

Based on Table 4.40, there are consistent results for the total and direct models in the Breusch-Pagan LM test and the Redundant Fixed Effect Test. The p-value of both tests for all models is 0.0000, indicating that the insufficient application of Pooled OLS over REM and FEM. Therefore, the Hausman Test is applied to choose between the REM and FEM by testing whether the individual effects are correlated with the regressors. However, the model selection results for the total and direct effect models are mixed, with some models favoring REM and others favoring FEM. Among all models, those that include BankTrans as the main independent variable consistently indicate REM as the preferred specification across all dependent variables. Notably, the inconsistency in preferred model choices between the total effect models and the direct effect models reflects the sensitivity of the model structure to the inclusion of the mediator. This shift suggests that introducing FDI changes the unobserved heterogeneity structure across countries, leading to different statistical assumptions being more appropriate in different model specifications. The detailed model selection results can be referred to in Table 4.40.

4.7.2 Diagnostic Check Results

4.7.2.1 Unit Root Test

Table 4.41: Summary of Unit Root Test Results of RQ6

Variable	**p-value [inverse chi-squared (110)]**	**Results**
Internet	0.0000	Stationery
BankTrans	0.0000	Stationery
Mobile	0.0000	Stationery
FDI	0.0000	Stationery

Based on Table 4.41, the p-value of the independent variables involved is all reported as 0.0000 in Augmented Dickey Fuller Tests. Therefore, the variable can be concluded as stationary and fulfils the first requirement of the regression model to ensure reliability of the estimation results.

4.7.2.2 Multicollinearity

Table 4.42: Summary of the Multicollinearity Test of RQ6

	vif					
Variable	**SDG Index**	**SDG 1**	**SDG 8**	**SDG 9**	**SDG 10**	**SDG 13**
(i) Total Effect						
INStartup	1.18	1.18	1.18	1.18	1.18	1.18
Startup	1.15	1.15	1.15	1.15	1.15	1.15
Income Level	1.03	1.03	1.03	1.03	1.03	1.03
INInternet	3.05	3.05	3.05	3.05	3.05	3.05
Internet	2.64	2.64	2.64	2.64	2.64	2.64
Income Level	1.74	1.74	1.74	1.74	1.74	1.74
INBankTrans	2.42	2.42	2.42	2.42	2.42	2.42
BankTrans	2.20	2.20	2.20	2.20	2.20	2.20
Income Level	1.27	1.27	1.27	1.27	1.27	1.27
INMobile	1.37	1.37	1.37	1.37	1.37	1.37
Mobile	1.31	1.31	1.31	1.31	1.31	1.31
Income Level	1.30	1.30	1.30	1.30	1.30	1.30
(ii) Direct Effect						
INStartup	1.18	1.18	1.18	1.18	1.18	1.18
Startup	1.15	1.15	1.15	1.15	1.15	1.15
Income Level	1.03	1.03	1.03	1.03	1.03	1.03
FDI	1.00	1.00	1.00	1.00	1.00	1.00
INInternet	3.06	3.06	3.06	3.06	3.06	3.06
Internet	2.64	2.64	2.64	2.64	2.64	2.64

Income Level	1.75	1.75	1.75	1.75	1.75	1.75
FDI	1.01	1.01	1.01	1.01	1.01	1.01
INBankTrans	2.44	2.44	2.44	2.44	2.44	2.44
BankTrans	2.23	2.23	2.23	2.23	2.23	2.23
Income Level	1.27	1.27	1.27	1.27	1.27	1.27
FDI	1.01	1.01	1.01	1.01	1.01	1.01
INMobile	1.37	1.37	1.37	1.37	1.37	1.37
Mobile	1.31	1.31	1.31	1.31	1.31	1.31
Income Level	1.30	1.30	1.30	1.30	1.30	1.30
FDI	1.00	1.00	1.00	1.00	1.00	1.00

Based on Table 4.42, the total and direct effect models have similar results in terms of multicollinearity. This is because both models use the same set of independent variables, with the direct effect model including only one additional variable (FDI). Based on the results, after mean-centering, the VIF value of all of the independent variables is below 5, indicating there is no multicollinearity among the independent variables. Therefore, it can be concluded that multicollinearity is not a concern for either model.

4.7.2.3 Heteroskedasticity

Similar to Section 4.6, as discussed in Section 4.7.1, the preferred models are REM and FEM, where the standard heteroskedasticity test is not applicable. However, due to the potential heteroscedasticity and within-cluster correlation, the cluster robust standard errors are applied to all models to ensure the reliability and robustness of the estimated regression results.

4.7.2.4 Autocorrelation

Table 4.43: Summary of Autocorrelation Results of RQ6

Variable	F-statistics	p-value	Results
(i) Total Effect			
DV: SDG Index			
Startup	131.374	0.0000	Autocorrelation detected
Internet	61.147	0.0000	Autocorrelation detected
BankTrans	99.171	0.0000	Autocorrelation detected
Mobile	123.589	0.0000	Autocorrelation detected
DV: SDG 1			
Startup	11.580	0.0013	Autocorrelation detected
Internet	11.031	0.0016	Autocorrelation detected
BankTrans	11.153	0.0015	Autocorrelation detected
Mobile	10.662	0.0019	Autocorrelation detected
DV: SDG 8			
Startup	118.904	0.0000	Autocorrelation detected
Internet	128.988	0.0000	Autocorrelation detected
BankTrans	138.405	0.0000	Autocorrelation detected
Mobile	105.759	0.0000	Autocorrelation detected
DV: SDG 9			
Startup	119.996	0.0000	Autocorrelation detected
Internet	44.283	0.0000	Autocorrelation detected
BankTrans	121.106	0.0000	Autocorrelation detected
Mobile	156.377	0.0000	Autocorrelation detected
DV: SDG 10			
Startup	22.718	0.0000	Autocorrelation detected
Internet	21.975	0.0000	Autocorrelation detected
BankTrans	22.092	0.0000	Autocorrelation detected
Mobile	22.233	0.0000	Autocorrelation detected

DV: SDG 13			
Startup	21.527	0.0000	Autocorrelation detected
Internet	14.570	0.0003	Autocorrelation detected
BankTrans	16.671	0.0001	Autocorrelation detected
Mobile	17.523	0.0001	Autocorrelation detected
(ii) Direct Effect			
DV: SDG Index			
Startup	134.304	0.0000	Autocorrelation detected
Internet	61.460	0.0000	Autocorrelation detected
BankTrans	100.521	0.0000	Autocorrelation detected
Mobile	126.964	0.0000	Autocorrelation detected
DV: SDG 1			
Startup	11.575	0.0013	Autocorrelation detected
Internet	11.024	0.0016	Autocorrelation detected
BankTrans	11.150	0.0015	Autocorrelation detected
Mobile	10.619	0.0019	Autocorrelation detected
DV: SDG 8			
Startup	118.764	0.0000	Autocorrelation detected
Internet	128.880	0.0000	Autocorrelation detected
BankTrans	138.373	0.0000	Autocorrelation detected
Mobile	105.535	0.0000	Autocorrelation detected
DV: SDG 9			
Startup	119.855	0.0000	Autocorrelation detected
Internet	44.378	0.0000	Autocorrelation detected
BankTrans	120.918	0.0000	Autocorrelation detected
Mobile	155.889	0.0000	Autocorrelation detected

DV: SDG 10			
Startup	23.511	0.0000	Autocorrelation detected
Internet	22.774	0.0000	Autocorrelation detected
BankTrans	22.910	0.0000	Autocorrelation detected
Mobile	23.082	0.0000	Autocorrelation detected
DV: SDG 13			
Startup	28.655	0.0000	Autocorrelation detected
Internet	17.921	0.0001	Autocorrelation detected
BankTrans	21.697	0.0000	Autocorrelation detected
Mobile	21.505	0.0000	Autocorrelation detected

Based on Table 4.43, the results of the Wooldridge Test are consistent for both total and direct effect models. The p-values of all models are reported with values of less than 0.05, indicating the presence of autocorrelation in all models. These results suggest that the error terms are correlated across time and the assumption of independence is violated. Therefore, a similar remedy is applied to the models by using cluster-robust standard errors. This adjustment is able to correct the standard errors for correlation within clusters over time, producing unbiased and consistent estimates.

In summary, due to the presence of potential heteroskedasticity and confirmed autocorrelation in all models, cluster-robust standard errors are applied to all specifications. This adjustment ensures that the coefficient estimates are unbiased and reliable, allowing for valid statistical inference.

4.7.3 Regression Analysis

4.7.3.1 FinTech Startup

Table 4.44: Regression Results of Total Effect Models for RQ6 – FinTech Startup

	Dependent Variable					
Statistics	**SDG Index**	**SDG 1**	**SDG 8**	**SDG 9**	**SDG 10**	**SDG 13**
Adjusted R-Squared	0.6326	0.1277	0.2768	0.0974	0.0096	0.4578
F-statistic (p-value)	118.02 0.0000	1.67 0.1987	75.41 0.0000	12.19 0.0000	2.40 0.1000	70.78 0.0000
Startup Coefficient t-statistic (p-value)	 -0.03596 *** -4.36 0.000	 -0.0380 * -1.82 0.074	 -0.0519 *** -6.44 0.000	 -0.1350 *** -4.81 0.000	 -0.0450 -1.64 0.106	 -0.0175 * -1.68 0.092
Income Level Coefficient t-statistic (p-value)	 7.8970 *** 8.92 0.000	 Omitted	 4.9170 *** 3.95 0.000	 Omitted	 Omitted	 -10.1259 *** -8.41 0.000
INStartup Coefficient t-statistic (p-value)	 -0.0079 -0.65 0.516	 0.0498 * 1.76 0.084	 0.0239 1.51 0.132	 0.0259 0.59 0.558	 0.06899 1.45 0.152	 -0.0663 *** -2.75 0.006
Constant Coefficient t-statistic (p-value)	 73.8055 117.55 0.000	 88.5064 1452.33 0.000	 73.7909 96.99 0.000	 60.7357 640.87 0.000	 66.9332 654.58 0.000	 83.4174 72.51 0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.44, the regression results examine the relationship between the independent variable, Startup, and the achievements of SDGs. A total of six models are included in this section. Overall, the explanatory power of the models varies, as do the significance levels of the variables. The results indicate that Startup has a significant effect on certain specific areas of SDG achievement at the average level, although its impact is not consistent across all dimensions. It is also important to note that in all of the FEMs, the income level variable is omitted due to its time-invariant nature, preventing the estimation of its within-country effect over time.

For the first model with the composite SDG Index as the dependent variable, the explanatory power of the model is relatively high, where 63.26% of the variation is explained by the model. In detail, the main independent variable, Startup, is highly significant in this model at 1% significance level. The coefficient of Startup further indicates that a one-unit increase in the number of Startup, the composite SDG Index is decreased by 0.0360, suggesting a negative relationship. Additionally, Income Level is also highly significant to the variation of SDG Index with a positive coefficient. These results indicate that the higher income level is associated with a higher SDG Index. In contrast, INStartup is not statistically significant, which means there is no evidence to have a meaningful moderating effect of income level for the relationship of Startup and SDG Index.

Moreover, in the second model, with the individual SDG 1 index as the dependent variable, the explanatory power is low, with an R-squared of 0.1277. The F-statistic indicates that the model is not statistically significant ($p = 0.1987$). Both Startup and the interaction term INStartup are marginally significant at the 10% level. The results suggest that Startup has a negative effect on SDG 1, and the effect of Startup slightly increases as income level rises. However, given the marginal significance, there is no strong evidence to support this relationship.

For the model with SDG 8 as the dependent variable, the R-squared is 0.2768, indicating that 27.68% of the variation in SDG 8 is explained by the model. Similar to the composite SDG Index model, both Startup and income level are individually statistically significant. Specifically, the results suggest a negative relationship between Startup and SDG 8, while income level has a positive effect. The interaction term is not statistically significant ($p > 0.05$), indicating no moderating effect of income level in this model.

In the model with SDG 9 as the dependent variable, explanatory power is relatively low compared to other models, with only 9.74% of the variation explained. Nevertheless, Startup is highly significant, holding other variables constant, and has a negative coefficient ($\beta = -0.1350$), indicating that a one-unit increase in Startup is associated with a 0.1350 decrease in SDG 9 on average. In contrast, income level and INStartup are not statistically significant, suggesting that neither the income level nor a moderating effect meaningfully influence SDG 9.

On the contrary, the model with SDG 10 as the dependent variable has the lowest explanatory power among the models in this section. None of the variables, including Startup, income level, or the interaction term, are statistically significant. Therefore, it can be concluded that Startup does not meaningfully affect SDG 10, either individually or through a moderating effect.

Finally, in the model with SDG 13 as the dependent variable, the R-squared is 0.4578, indicating that 45.78% of the variation is explained by the model, which is statistically significant at the 1% level. However, Startup is only marginally significant ($p = 0.092$) and has a negative coefficient, suggesting a negative relationship with SDG 13, though this effect is not strongly supported. In contrast, income level is highly significant, highlighting that SDG 13 scores largely depend on income level. The interaction term INStartup is also highly significant, indicating that the effect of Startup on SDG 13 decreases as income level increases. While the individual effect of Startup is not significant, the moderating effect demonstrates that its impact is conditional on income level.

Table 4.45: Regression Results of Direct Effect Models for RQ6 – FinTech Startup

	Dependent Variable					
Statistics	**SDG Index**	**SDG 1**	**SDG 8**	**SDG 9**	**SDG 10**	**SDG 13**
Adjusted R-Squared	0.6327	0.5608	0.2779	0.0946	0.2091	0.4572
F-statistic	179.94	33.61	89.57	8.10	23.39	73.20
(p-value)	0.0000	0.0000	0.0000	0.0002	0.0001	0.0000
<u>Startup</u>						
Coefficient	-0.0359 ***	-0.0362 *	-0.0517 ***	-0.1351 ***	-0.0500 *	-0.0173 *
t-statistic	-4.35	-1.77	-6.42	-4.80	-1.86	-1.66
(p-value)	0.000	0.077	0.000	0.000	0.063	0.097
<u>Income Level</u>						
Coefficient	7.8978 ***	19.4134 ***	4.9200 ***	Omitted	16.2635 ***	-10.1223 ***
t-statistic	8.91	5.58	3.95		3.87	-8.40
(p-value)	0.000	0.000	0.000		0.000	0.000
<u>INStartup</u>						
Coefficient	-0.0077	0.0442	0.0249	0.0257	0.0800 *	-0.0657 ***
t-statistic	-0.64	1.57	1.54	0.58	1.69	-2.73
(p-value)	0.522	0.117	0.123	0.563	0.091	0.006
<u>FDI</u>						
Coefficient	-0.0004 ***	0.0003	-0.0015 ***	0.0007	-0.0007 *	-0.0018
t-statistic	-4.21	1.26	-3.56	0.50	-1.95	0.74
(p-value)	0.000	0.206	0.000	0.621	0.051	0.458
<u>Constant</u>						
Coefficient	73.8065	88.5175	73.79	60.7339	66.9119	83.4222
t-statistic	117.42	49.09	96.91	641.17	19.49	72.45
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

In the direct effect models that with Startup as the main independent variable, the mediator, FDI, is only significant in the models that with composite SDG Index and SDG 8 as the dependent variable. Focusing on the mediating effects, only these models have the potential to mediate the effects between Startup and the achievements of SDGs. However, as mentioned, Startups do not have a significant effect on FDI. Therefore, FDI cannot act as a mediator in the relationship between Startups and the achievement of SDGs, even though Startups are statistically significant for the composite SDG Index and SDG 8.

Therefore, in short, the mediator, FDI, does not have a mediating effect in the relationship between Startup and the achievement of SDGs. These results further suggest that the effect of FinTech on SDGs operates primarily through direct effects rather than through FDI. Combining the results of the total and direct effect models, the impact of Startup is most pronounced on the composite SDG Index, SDG 8, and SDG 9, while effects on other SDGs remain marginally significant.

4.7.3.2 Internet

Table 4.46: Regression Results of Total Effect Models for RQ6– Internet

	Dependent Variable					
Statistics	**SDG Index**	**SDG 1**	**SDG 8**	**SDG 9**	**SDG 10**	**SDG 13**
Adjusted R-Squared	0.6963	0.7170	0.3511	0.7426	0.1671	0.3284
F-statistic (p-value)	224.03 0.0000	6.97 0.0020	31.49 0.0000	71.45 0.0000	4.12 0.0216	4.69 0.0132
Internet Coefficient	0.0715	0.0450	0.0765	0.3573	0.1165	-0.0573

	***	**	***	****	**	*
t-statistic	8.75	2.63	3.72	11.86	2.52	81.82
(p-value)	0.000	0.011	0.000	0.000	0.015	0.074
Income Level						
Coefficient	6.7175 ***	Omitted	3.9115 ***	Omitted	Omitted	Omitted
t-statistic	7.56		3.16			
(p-value)	0.000		0.002			
INInternet						
Coefficient	0.0188	-0.0788 **	0.0498 **	0.0819	0.0868 **	-0.0423
t-statistic	1.53	-2.44	1.98	1.51	2.58	-1.08
(p-value)	0.127	0.018	0.047	0.136	0.013	0.283
Constant						
Coefficient	73.5650	89.5509	73.2499	59.8166	66.0487	83.7778
t-statistic	121.53	233.18	88.77	92.84	164.80	180.47
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.46, the regression results indicate that Internet development is overall significant in explaining the achievement of the SDGs, with relatively strong explanatory power across most models. Specifically, the Internet variable is highly significant for the majority of SDG outcomes, except for SDG 13. This suggests that while Internet development contributes meaningfully to most sustainability outcomes, its impact on climate-related indicators is not statistically supported.

In the first model, where the SDG Index is the dependent variable, the model demonstrates high explanatory power, accounting for 69.63% of its variation. Both Internet and Income Level are highly significant ($p = 0.0000$), and Internet has a positive coefficient, where a one-unit increase leads to a 0.0715 increase in the SDG Index. However, the moderating effect is not significant ($p > 0.05$), indicating that the impact of the Internet operates directly rather than through interaction with income level.

For the model with SDG 1 as the dependent variable, the model maintains high explanatory power with an R-squared of 0.7170, and the overall model remains highly significant. Both the Internet and the interaction term, INInternet, are statistically significant at 5% level. The Internet shows a positive effect, where each additional unit increases SDG 1 by 0.0450. However, the negative coefficient of the interaction term indicates that this positive effect weakens as income level increases.

Similar to the model with SDG 8 as the dependent variable, the model shows moderate explanatory power, explaining 35.11% of the variation and is significant at the 1% level. All independent variables are significant in this model. Notably, both Internet and Income Level are highly significant at 1% level and show positive effects to SDG 8. The interaction term, which is INInternet, is also positive, suggesting that the beneficial impact of Internet on SDG 8 strengthens as income level rises, which is opposite to the case of SDG 1.

Furthermore, the model with SDG 9 as the dependent variable recorded the highest explanatory power, with an R-squared of 0.7426. In this model, the Internet is the only variable that is significant at 1% level. In the meantime, among the models in this section, the Internet has a notably large coefficient, where each one-unit increase in Internet corresponds to a 0.3573 increase in SDG 9. However, the moderating effect remains insignificant, indicating no meaningful interaction between Internet and income level in this context.

Moreover, for the model with SDG 10 as the dependent variable, the model's explanatory power is relatively low, where only 16.71% of the variation of SDG 10 is explained by this model. Nevertheless, both Internet and INInternet are significant with positive coefficients, suggesting a positive relationship. In detail, a one-unit increase in Internet will increase SDG 10 by 0.1165.

Additionally, the positive effect of the Internet on SDG 10 will increase as the income level increases.

Finally, for SDG 13, the model exhibits moderate explanatory power (32.84%), but none of the independent variables are statistically significant. This further supports the conclusion that Internet development does not meaningfully explain climate-related outcomes. The non-significance of the interaction term reinforces the lack of a moderating effect by income level.

Table 4.47: Regression Results of Direct Effect Models for RQ6– Internet

	Dependent Variable					
Statistics	**SDG Index**	**SDG 1**	**SDG 8**	**SDG 9**	**SDG 10**	**SDG 13**
Adjusted R-Squared	0.6963	0.7173	0.3512	0.7429	0.2165	0.3191
F-statistic (p-value)	224.03 0.0000	5.26 0.0030	33.81 0.0000	48.06 0.0000	28.79 0.0000	3.43 0.0232
Internet						
Coefficient	0.0714 ***	0.0451 **	0.0760 ***	0.3585 ***	0.1217 ***	-0.0584 *
t-statistic	8.71	2.62	3.68	11.90	2.65	-1.85
(p-value)	0.000	0.011	0.000	0.000	0.008	0.069
Income Level						
Coefficient	6.7176 ***	Omitted	3.9134 ***	Omitted	14.8330 ***	Omitted
t-statistic	7.55		3.16		3.56	
(p-value)	0.000		0.002		0.000	
INInternet						
Coefficient	0.0188	-0.0786 **	0.0493 *	0.0833	0.0953 ***	-0.0436
t-statistic	1.52	-2.43	1.95	1.54	2.93	-1.12
(p-value)	0.129	0.019	0.051	0.129	0.003	0.270
FDI						
Coefficient	-0.0001	0.0003	-0.0010	0.0028 ***	0.0005	-0.0028
t-statistic	-0.10	0.93	-1.11	3.83	0.56	-1.10

(p-value)	0.924	0.357	0.265	0.000	0.572	0.278
Constant						
Coefficient	73.5655	89.5481	73.2593	59.7912	65.9458	83.8026
t-statistic	121.33	232.6	88.64	92.84	19.11	179.65
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Throughout the direct effects model, the mediator, FDI is only statistically significant when SDG9 is the dependent variable. This suggests that SDG9 is the only model with a potential mediating effect through FDI. In contrast, for all other SDGs, the insignificant results confirm that FDI does not meaningfully explain the variation in the achievement of these SDGs, consistent with the absence of any mediating effect. However, the main independent variable, Internet, has no significant effect on FDI, as shown in Section 4.3. This indicates that no mediating effect of FDI on the relationship between the Internet and achievements of SDGs is possible.

Therefore, overall, the results indicate that FDI does not mediate the relationship between the Internet and the achievement of the SDGs. Focusing on the relationship, the Internet has a strong effect on the achievement of SDGs, except for SDG 13, particularly with a positive coefficient. These results further suggest that the Internet is beneficial and serves as a key predictor for the advancement of SDGs.

4.7.3.3 BankTrans

Table 4.48: Regression Results of Total Effect Models for RQ6– BankTrans

	Dependent Variable

Statistics	SDG Index	SDG 1	SDG 8	SDG 9	SDG 10	SDG 13
Adjusted R-Squared	0.6512	0.5992	0.3515	0.6001	0.2161	0.4708
F-statistic (p-value)	107.68 0.0000	43.14 0.0000	23.26 0.0000	97.30 0.0000	31.03 0.0000	93.25 0.0000
BankTrans						
Coefficient	0.4342 **	0.1991	0.5950 **	2.1342 **	0.7146 *	-0.4256
t-statistic	2.55	1.25	2.50	2.40	1.87	-1.40
(p-value)	0.011	0.210	0.013	0.016	0.062	0.162
Income Level						
Coefficient	7.1700 ***	17.6916 ***	4.2640 ***	18.1785 ***	15.7551 ***	-9.5439 ***
t-statistic	6.80	5.11	3.29	5.64	3.91	-7.56
(p-value)	0.000	0.000	0.001	0.000	0.000	0.000
INBankTrans						
Coefficient	0.1070	-0.7048 *	0.4888 **	0.2881	0.8985 ***	-0.2894
t-statistic	0.76	-1.93	2.04	0.56	2.77	-0.75
(p-value)	0.446	0.054	0.041	0.573	0.006	0.454
Constant						
Coefficient	73.6672	89.4132	73.2878	60.4646	66.0623	83.6030
t-statistic	112.21	48.71	92.32	28.21	19.60	63.52
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.48, the regression results reveal that the specific indicator, BankTrans, has a statistically significant effect on the composite SDG Index as well as on SDG 8 and SDG 9. This indicates that the effect of BankTrans is significant only in certain areas of sustainable development, particularly economic growth and infrastructure development. At the same time, the explanatory power and significance levels of these six models remain high, highlighting the important role of BankTrans in FinTech development in affecting the achievement of SDGs.

For the first model with composite SDG Index as the dependent variable, the explanatory power of the model is high, with 65.12% of the variation of the model is explained by the model. Focusing on the individual contribution, BankTrans and Income Level both are significant in the model, except for the interaction term, INBankTrans. Specifically, BankTrans is statistically significant at the 5% level with a positive coefficient of 0.4342, suggesting that a 1% increase in BankTrans may lead to a 0.4342 increase in the SDG Index. The non-significance of INBankTrans indicates that the effect of BankTrans is primarily direct rather than moderated by income level.

In the model with SDG 8 as the dependent variable, the model is highly significant, with moderate explanatory power, with an R-squared of 0.3515. All independent variables in this model are significant with positive coefficients. The increase of 1 % of BankTrans, the SDG 8 will increase by 0.5950 simultaneously. Notably, the positive coefficient of the interaction term, INBankTrans, suggests that the positive effect of BankTrans on SDG 8 increases as income level rises, indicating a moderating effect.

For the model with SDG 9 as the dependent variable, the explanatory power is high with an R-squared of 0.6001, and the overall model is highly significant at the 1% level. The positive coefficient of BankTrans indicates that a 1% increase in BankTrans contributes to a 2.1342 increase in the SDG 9 score, which is a large effect size. However, the interaction term, INBankTrans is not statistically significant, suggesting the effect of BankTrans is primarily direct.

For the other models, BankTrans alone does not significantly impact the variation in SDGs, particularly SDG 1, SDG 10, and SDG 13. However, BankTrans has a marginally significant effect on SDG 13, and the positive coefficient of the interaction term, INBankTrans in this model suggests that the effect of BankTrans may increase as income level rises. Nevertheless, the evidence remains weak, so the relationship is considered not meaningful.

Table 4.49: Regression Results of Direct Effect Models for RQ6– BankTrans

	Dependent Variable					
Statistics	**SDG Index**	**SDG 1**	**SDG 8**	**SDG 9**	**SDG 10**	**SDG 13**
Adjusted R-Squared	0.6512	0.5992	0.3513	0.6004	0.2163	0.4711
F-statistic (p-value)	111.67 0.0000	43.16 0.0000	25.34 0.0000	88.44 0.0000	30.79 0.0000	94.77 0.0000
BankTrans						
Coefficient	0.4351 **	0.1984	0.5921 **	2.1578 **	0.7231 *	-0.4467
t-statistic	2.52	1.24	2.46	2.39	1.86	-1.44
(p-value)	0.012	0.216	0.014	0.017	0.063	0.149
Income Level						
Coefficient	7.1696 ***	17.6921 ***	4.2632 ***	18.1790 ***	15.7519 ***	-9.5455 ***
t-statistic	6.78	5.10	3.28	5.63	3.90	-7.53
(p-value)	0.000	0.000	0.001	0.000	0.000	0.000
INBankTrans						
Coefficient	0.1078	-0.7054 *	0.4844 **	0.3212	0.9077 ***	-0.3190
t-statistic	0.76	-1.91	1.99	0.62	2.77	-0.82
(p-value)	0.447	0.056	0.047	0.533	0.006	0.415
FDI						
Coefficient	0.0001	-0.0001	-0.0004	0.0034 **	0.0012	-0.0031
t-statistic	0.29	-0.22	-0.39	2.20	1.33	-1.23
(p-value)	0.773	0.823	0.696	0.028	0.184	0.220

Constant						
Coefficient	73.6658	89.4141	73.2941	60.4172	66.0480	83.6468
t-statistic	112.02	48.59	91.91	28.14	19.59	64.01
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

In the total effects model, BankTrans has a statistically significant effect on the composite SDG Index, SDG 8, and SDG 9. However, in the direct effect models that include the mediator FDI, FDI is significant only in the model where SDG 9 is the dependent variable, making it the only model with potential mediating effects of FDI. As shown in Section 4.3, BankTrans does not have a statistically significant effect on FDI. Therefore, FDI does not mediate the relationship between BankTrans and any SDG achievement, neither partially nor fully.

In short, it can be concluded that FDI does not mediate the relationship between BankTrans and the achievement of SDGs. Similarly, combining the total and direct effect models, BankTrans is significantly major on the achievement of composite SDG Index, SDG 8 and SDG 9, and potentially for the SDG 10. In contrast, there is no supporting evidence for the effect of BankTrans on the achievement of other SDGs. These results further highlight that the impact of BankTrans is more pronounced in the areas of economic performance, infrastructure, and innovation.

4.7.3.4 Mobile

Table 4.50: Regression Results of Total Effect Models for RQ6– Mobile

	Dependent Variable					
Statistics	**SDG Index**	**SDG 1**	**SDG 8**	**SDG 9**	**SDG 10**	**SDG 13**
Adjusted R-Squared	0.0300	0.4225	0.2814	0.5702	0.1853	0.4573

F-statistic (p-value)	1.78 0.1789	0.76 0.4737	25.76 0.0000	84.50 0.0000	14.63 0.0022	95.13 0.0000
Mobile Coefficient t-statistic (p-value)	 0.0191 * 1.88 0.065	 0.0087 0.37 0.710	 0.0466 *** 3.20 0.001	 0.1047 ** 2.33 0.020	 0.0032 0.07 0.944	 -0.0341 -1.21 0.226
Income Level Coefficient t-statistic (p-value)	 Omitted	 Omitted	 4.5501 *** 3.64 0.000	 20.3898 *** 7.23 0.000	 15.9033 *** 3.78 0.000	 -9.7178 *** -7.99 0.000
INMobile Coefficient t-statistic (p-value)	 0.0039 0.29 0.770	 -0.0443 -1.21 0.233	 0.0378 *** 2.64 0.008	 -0.0115 -0.22 0.826	 0.0177 0.63 0.530	 -0.0172 -0.55 0.583
Constant Coefficient t-statistic (p-value)	 73.7625 828.91 0.000	 88.9125 358.65 0.000	 73.5874 96.26 0.000	 60.8689 30.24 0.000	 66.9618 19.31 0.000	 83.3906 68.30 0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Based on Table 4.50, the regression results illustrate the direct impact of Mobile on the achievement of the SDGs. The explanatory power of the models is relatively strong, except for the composite SDG Index. Mobile is statistically significant only in the models for SDG 8 and SDG 9, indicating that mobile development contributes specifically to sustainability dimensions related to economic performance and infrastructure enhancement.

Focusing on the significant models, the explanatory power of the SDG 8 model is moderate, with 28.14% of the variation in SDG 8 explained by the included variables. Mobile, Income Level, and the interaction term, INMobile, are all highly significant at the 1% level, underscoring the relevance of this specification. Mobile has a positive effect on the achievement of SDG 8, supported by its coefficient of 0.0466. The significant and positive INMobile further implies that the beneficial effect of Mobile intensifies as income levels increase, suggesting a meaningful moderating role of income level.

The model with SDG 9 as the dependent variable exhibits a comparatively high explanatory power, with 57.02% of its variation accounted for. Mobile is statistically significant at the 5% level in this model, confirming its positive contribution to SDG 9. The coefficient of 0.1047 indicates that a one-unit increase in Mobile is associated with a 0.1047 increase in the SDG 9 score. However, INMobile is not statistically significant, implying that the relationship between Mobile and SDG 9 operates primarily through a direct effect rather than being conditioned by income level.

For the models with the composite SDG Index, SDG 1, SDG 10, and SDG 13, Mobile does not exhibit statistical significance. This suggests that Mobile does not exert a meaningful influence on these SDGs, regardless of whether the estimated coefficients are positive or negative. Nonetheless, income level remains consistently significant across these models, reinforcing its importance as a structural determinant of sustainable development outcomes.

Table 4.51: Regression Results of Direct Effect Models for RQ6– Mobile

	Dependent Variable					
Statistics	**SDG Index**	**SDG 1**	**SDG 8**	**SDG 9**	**SDG 10**	**SDG 13**
Adjusted R-Squared	0.0317	0.4225	0.2826	0.5701	0.1854	0.4569
F-statistic (p-value)	5.41 0.0025	1.04 0.3833	33.22 0.0000	84.91 0.0000	17.66 0.0014	98.21 0.0000

Mobile						
Coefficient	0.0190	0.0087	0.0462 ***	0.1049 **	0.0030	-0.0350
t-statistic	1.86	0.37	3.16	2.32	0.07	-1.24
(p-value)	0.68	0.710	0.002	0.020	0.947	0.213
Income Level						
Coefficient	Omitted	Omitted	4.492 ***	20.3909 ***	15.9041 ***	-9.7197 ***
t-statistic			3.64	7.22	3.78	-7.97
(p-value)			0.000	0.000	0.000	0.000
INMobile						
Coefficient	0.0036	-0.0443	0.0372 **	-0.0112	0.0176	-0.0185
t-statistic	0.28	-1.20	2.59	-0.21	0.62	-0.59
(p-value)	0.784	0.235	0.010	0.831	0.535	0.555
FDI						
Coefficient	-0.0004 **	-0.0001	-0.0011 **	0.0006	-0.0006	-0.0025
t-statistic	-2.09	0.07	-2.12	0.58	-1.04	-0.94
(p-value)	0.041	0.942	0.034	0.560	0.298	0.347
Constant						
Coefficient	73.7654	88.9123	73.5951	60.8646	66.9646	83.4077
t-statistic	823.83	356.88	96.20	30.20	19.29	68.59
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000

****, **, or * beside the coefficient denotes a significant relationship at 0.01, 0.05, or 0.10, respectively.*

Table 4.51 presents the regression results of the direct effect models with Mobile as the main independent variable. Overall, FDI is statistically significant in the models with the composite SDG Index and SDG 8 as the dependent variables, indicating potential mediating effects of FDI in these models. However, although Mobile has a significant effect on SDG 8, Section 4.3 shows that Mobile does not significantly affect FDI. Therefore, there is no potential mediating effect of FDI in the relationship between Mobile and any SDG achievement.

Therefore, it can be concluded that FDI does not exert a meaningful mediating effect on the relationship between Mobile and the achievement of the SDGs. Besides, another key finding is that all the models above report a highly significant effect of income level on SDG achievement, except for the model that utilizes FEM. These results suggest that income level is an important structural factor influencing SDGs achievement, and its effect persists regardless of the level of FinTech development. Combining with the results, FinTech development indicators, Mobile has a limited effect on the achievement of SDGs, with only significant effects on SDG 8 and SDG 9. These results further indicate that the impact of Mobile is more significant in the area of economic growth and infrastructure development.

Overall, FinTech development generally has a significant and positive effect on the achievement of SDGs, except for SDG 13. This further indicates that the effects of FinTech development are more pronounced in the economic and social dimensions. However, it is also notable that the results for FinTech startups reveal a negative coefficient, suggesting inefficiencies in translating startup activity into sustainable development outcomes. While most FinTech development indicators show significant effects in the economic and social dimensions, particularly SDG 1, SDG 8, SDG 9, and SDG 10. These results are consistent with Innovation Diffusion Theory and the findings of Choudhary et al. (2025), Lee et al. (2024), and Salleh et al. (2025). Nevertheless, some theoretical contradictions remain. In particular, Complex Systems Theory suggests more heterogeneous and nonlinear effects, which is also reflected in the insignificant or weaker effects at higher percentiles reported by Choudhary et al. (2025). Focusing on the environmental dimension, the insignificant results for SDG 13 are further consistent with Complex Systems Theory. However, the findings for SDG 13 largely contradict existing empirical studies, such as Uddin et al. (2024), Croutzet and Dabbous (2021), and Zhang et al. (2024).

4.8 Summary of Hypothesis

Table 4.52: Summary of Hypothesis Testing Results

Hypothesis	Support	Remarks	Citation
H1: There are significant differences in FinTech development among low-income, lower-middle-income, upper-middle-income, and high-income economies.	Supported		**Consistent:** Alvarado et al., 2017; Demir et al., 2022; Sayari et al., 2025 **Contradict:** Choudhary et al., 2025; Demir et al., 2022
H2: FinTech development positively impacts Foreign Direct Investment across low-income, lower-middle-income, upper-middle-income, and high-income economies.	Not supported	The effect is not statistically significant	**Consistent:** Uddin et al., 2024; Jiang et al.,2024 **Contradict:** Al-Smadi &Al-Smadi., 2024
H3a: FDI positively impacts Households and NPISH Final Consumption Expenditure (HFCE) across low-income, lower-middle-income, upper-middle-income, and high-income economies.	Supported		**Consistent:** Luo, Sun, & Zhou, 2022; Ochirova & Miriakov, 2025 **Contradict:** Alvarado et al., 2017

H3b: FDI positively impacts the GDP Growth across low-income, lower-middle-income, upper-middle-income, and high-income economies.	Not supported	The effect is not statistically significant	**Consistent:** Azman-Saini et al., 2010; Alvarado et al., 2017; Mahmoodi & Mahmoodi., 2016 **Contradict:** Al-Smadi &Al-Smadi., 2024; Alvarado et al., 2017
H3c: FDI negatively impacts the unemployment rate across low-income, lower-middle-income, upper-middle-income, and high-income economies.	Not supported	The effect is not statistically significant	**Consistent:** Mahmoodi & Mahmoodi, 2016 **Contradict:** Alvarado et al., 2017; An et al., 2025
H3d: FDI positively impacts the gross fixed capital formation across low-income, lower-middle-income, upper-middle-income, and high-income economies.	Supported		**Consistent:** Alvarado et al., 2017; Ochirova & Miriakov, 2025 **Contradict:** Bermejo Carbonell & Werner, 2018
H3e: FDI negatively impacts the Carbon dioxide (CO_2) emissions across low-income,	Not Supported	The effect is not statistically significant	**Consistent:** Uddin et al., 2024 **Contradict:**

lower-middle-income, upper-middle-income, and high-income economies.			Zhang et al., 2024; Rodríguez-Chávez et al., 2024
H4a: Fintech development positively impacts Households and NPISH Final Consumption Expenditure (HFCE) across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI	Not Supported	The effect is not statistically significant	**Consistent:** Luo, Sun, & Zhou, 2022 **Contradict:** -
H4b: Fintech development positively impacts GDP growth across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI	Not Supported	The effect is not statistically significant	**Consistent:** Choudhary et al., 2025; Liu & Chu, 2024 **Contradict:** Choudhary et al., 2025
H4c: Fintech development negatively impacts the unemployment rate across low-income, lower-middle-income, upper-middle-income, and high-income	Supported	• BankTrans: negative effect • Startup: positive effect • Internet & Mobile:	**Consistent:** Choudhary et al., 2025 **Contradict:** Luo, Sun, & Zhou, 2022

economies through the mediating role of FDI		insignificant effect	
H4d: Fintech development positively impacts the gross fixed capital formation across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI	Not Supported	The effect is not statistically significant	**Consistent:** Satyanand, 2021 **Contradict:** Choudhary et al., 2025
H4e: Fintech development negatively impacts the Carbon dioxide (CO2) emissions across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI	Not Supported	The effect is not statistically significant	**Consistent:** Rahman et al., 2025 **Contradict:** Uddin et al., 2024; Zhang et al., 2024
H5a: FDI positively impacts the Composite SDG Index Score across low-income, lower-middle-income, upper-middle-income, and high-income economies.	Not Supported	FDI: negative effect	**Consistent:** Rodríguez-Chávez et al., 2024 **Contradict:** -
H5b: FDI positively impacts SDG 1 across low-income, lower-middle-income, upper-	Not Supported	The effect is not statistically significant	**Consistent:** - **Contradict:** -

middle-income, and high-income economies.			
H5c: FDI positively impacts SDG 8 across low-income, lower-middle-income, upper-middle-income, and high-income economies.	Not Supported	The effect is not statistically significant	**Consistent:** Alvarado et al., 2017 **Contradict:** Al-Smadi &Al-Smadi., 2024
H5d: FDI positively impacts SDG 9 across low-income, lower-middle-income, upper-middle-income, and high-income economies.	Not Supported	The effect is not statistically significant	**Consistent:** Alvarado et al., 2017 **Contradict:** Azman-Saini et al., 2010
H5e: FDI positively impacts SDG 10 across low-income, lower-middle-income, upper-middle-income, and high-income economies.	Not Supported	The effect is not statistically significant	**Consistent:** Alvarado et al., 2017; Rodríguez-Chávez et al., 2024 **Contradict:** Satyanand, 2021
H5f: FDI positively impacts SDG 13 across low-income, lower-middle-income, upper-middle-income, and high-income economies.	Not Supported	The effect is not statistically significant	**Consistent:** Uddin et al., 2024 **Contradict:**

			Zhang et al., 2024; Rodríguez-Chávez et al., 2024
H6a: Fintech development positively impacts the Composite SDG Index Score across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI	Supported	• Internet & BankTrans: positive effect • Startup: negative effect • Mobile: insignificant effect	**Consistent:** Choudhary et al., 2025 **Contradict:**
H6b: Fintech development positively impacts SDG 1 across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI	Supported	• Internet: positive effect • Startup, BankTrans & Mobile: insignificant effect	**Consistent:** Choudhary et al., 2025 **Contradict:** Demir et al., 2022
H6c: Fintech development positively impacts SDG 8 across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI	Supported	• Internet, BankTrans & Mobile: positive effect • Startup: negative effect	**Consistent:** Liu & Chu, 2024 **Contradict:** Choudhary et al., 2025
H6d: Fintech development positively	Supported	• Internet, BankTrans	**Consistent:** Lee et al., 2024

impacts SDG 9 across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI		& Mobile: positive effect • Startup: negative effect	**Contradict:** Choudhary et al., 2025
H6e: Fintech development positively impacts SDG 10 across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI	Supported	• Internet, BankTrans & Mobile: positive effect • Startup: negative effect	**Consistent:** Demir et al., 2022 **Contradict:** Luo, Sun, & Zhou, 2022
H6f: Fintech development positively impacts SDG 13 across low-income, lower-middle-income, upper-middle-income, and high-income economies through the mediating role of FDI	Not Supported	The effect is not statistically significant	**Consistent: -** **Contradict:** Uddin et al., 2024, Croutzet and Dabbous, 2021; Zhang et al., 2024

4.9 Chapter Summary

In summary of Chapter 4, the discussion begins with Descriptive Analysis. Overall, the variables FDI and CO2 have a higher variability compared with others. However, no logarithmic or other data transformations were applied to maintain accuracy and reflect real-world conditions. In terms of diagnostic tests, none of the models suffer from serious violations of the classical assumptions, except for heteroskedasticity and autocorrelation. To address these issues, cluster-robust standard errors were applied to ensure the reliability of the estimated results.

Based on the data analysis, the results from the Kruskal–Wallis test support the hypothesis, indicating that significant differences in FinTech development exist across income-level economies. FinTech indicators, including Startup, Internet, BankTrans, and Mobile, generally show an increasing pattern as income levels rise. However, an insignificant difference is observed between upper-middle- and high-income economies for the Mobile variable, suggesting a possible saturation effect at higher levels of development. In addition, FinTech development remains limited and relatively similar among lower-income economies, particularly low- and lower-middle-income countries.

Moreover, the analysis indicates no statistically significant relationship between FinTech development and FDI inflows across income levels, and therefore Hypothesis 2 is not supported. Although the results are insignificant, they remain aligned with existing studies suggesting that FinTech is still in an early stage of development, with a relatively limited impact on global investment indicators.

Furthermore, the direct effect of FDI on macroeconomic performance is found to be limited. FDI shows statistically significant effects only on HFCE and GFCF, which aligns with theoretical expectations that FDI stimulates consumption and capital accumulation. In contrast, the effects of FDI on other macroeconomic indicators are insignificant, reinforcing the view that the benefits of FDI are highly dependent on a country's absorptive capacity and structural conditions, consistent with Absorptive Capacity Theory.

The results also reveal that the mediating role of FDI between FinTech development and macroeconomic performance is not statistically significant, suggesting that the relationship is predominantly direct. Specifically, two FinTech indicators, Startup and BankTrans, have statistically significant effects on unemployment, but in opposite directions. The findings suggest that FinTech startups may not automatically reduce unemployment in the short term, while transactional banking FinTech can contribute positively to labour market outcomes by increasing economic activity, particularly through online business expansion.

With respect to Research Question 5, which examines the effect of FDI on SDG achievement, the analysis concludes that FDI does not have a statistically significant impact on either the composite SDG Index or any of the individual SDGs examined in this study. This insignificance is likely due to constraints such as institutional quality and sectoral concentration of FDI, which is consistent with the results observed for macroeconomic performance.

Finally, although the effects of FinTech on short-term economic performance are relatively limited, FinTech development demonstrates statistically significant impacts on SDGs achievement, except for SDG 13. Overall, FinTech development generally exhibits a positive influence on SDG outcomes, particularly in the economic and social dimensions. However, the FinTech Startup variable shows negative effects on SDG 8 and SDG 9, indicating potential short-term challenges and inefficiencies in translating startup activity into sustainable development outcomes.

CHAPTER 5: CONCLUSION

5.0 Introduction

This chapter summarizes the key findings based on the regression results presented in Chapter 4. A more comprehensive analysis is provided by adapting the empirical results to real-world contexts, thereby further supporting the observed patterns of findings. Furthermore, this chapter deepens the discussion on the relationships between FinTech development, FDI, macroeconomic performance, and the achievement of the SDGs, highlighting their broader significance. Based on these findings, the implications of this research, particularly in terms of policy and practical contributions, are outlined, with specific relevance to government policymakers, the traditional financial sector, and the FinTech industry. However, this research remains subject to certain limitations; therefore, recommendations for future research are also proposed in this chapter.

5.1 Summary of Key Findings

5.1.1 Research Question 1

Based on the Dunn Test results in Section 4.2.2, the findings are generally consistent with Hypothesis 1, supporting a significant difference in FinTech development across low-income, lower-middle-income, upper-middle-income, and high-income economies, specifically in terms of FinTech startups, Internet penetration, mobile and bank transfers, and mobile cellular subscriptions. The overall significance difference results further confirm that income level is associated with FinTech development. The imbalance across income groups may be explained by factors such as political instability, limited resources, and strong competition from more advanced markets. These constraints contribute to disparities in infrastructure quality, technological adoption, and financial literacy. As a result, lower-income communities are less able to fully benefit from FinTech-enabled financial services. In addition, the lower absorption capacity in these economies restricts their ability to effectively utilize and scale FinTech innovations. In contrast, higher-income economies typically demonstrate stronger FinTech development due to their more advanced infrastructure, greater technological readiness, and higher levels of financial literacy.

On the contrary, there is also a notable finding that the difference of FinTech indicators, which are Startup, Internet, and BankTrans, is not significant for the comparison group of low-income and lower-middle-income groups. These results further indicate that the financial technology ecosystem of both income economies is generally at an early stage of development. Countries in these categories often share similar structural limitations, such as limited venture capital availability, small-scale financial markets, and slower overall FinTech expansion (World Bank, 2022). At the same time, similar socio-economic challenges are faced by both categories, reducing the variability in FinTech adoption outcomes across the two groups. However, it is notable that the result might be subject to bias, as the low-income group includes only Rwanda.

In addition, there are also insignificant results in the difference between Mobile in the upper-middle-income and high-income groups. This pattern reflects a saturation effect in mobile technology adoption. Mobile phone usage and network coverage are already highly widespread in these economies, approaching a maximum level (Clavijo & Pantaleón, 2020; United Nations, 2025). Therefore, the incremental gain in mobile adoption becomes limited, especially for high-income economies. Moreover, compared with other FinTech technologies, mobile technology is older, more accessible, and more affordable. Therefore, it reduces the disparities at higher development levels and further causes no meaningful difference between upper-middle-income and high-income communities.

5.1.2 Research Question 2

Based on the analysis results in Section 4.3.3, FinTech development does not have a significant effect on FDI. Therefore, it can be concluded that there is no meaningful relationship between FinTech development and FDI in the sample. As mentioned earlier, the insignificant findings are consistent with the results reported by Jiang et al. (2024). Their study suggests that such insignificant effects may arise from the relatively small scale and nascent stage of the FinTech sector in many countries. In detail, the FinTech sector is still in its infancy and relatively small in size compared to the traditional or general financial services; therefore, it restricted impact on major economic channels, including FDI inflow. At the same time, due to the limited size of the FinTech sector, its influence on attracting or substituting for foreign capital is still limited and not very noticeable. This is especially true as FDI flows are generally large and well-established compared to the emerging scale of FinTech activities (Mashamba et al., 2023).

Additionally, the insignificant effect is also possibly due to the conflicting economic impact, where FinTech simultaneously has the impact of attracting and repelling on the FDI flow. These opposing forces will further neutralize the overall effect. This explanation is also supported by Jiang et al. (2024), who argue that FinTech has both promotional effects and inhibitory effects on FDI inflow at the same time. In detail, FinTech development is able to attract FDI inflow due to the enhancement of financial efficiency and qualitative development. In contrast, FinTech development also minimizes the demand for foreign capital in the host economy by effectively combining domestic funds and reducing financial exclusion. This is supported by the rise of FinTech innovation, such as equity crowdfunding, P2P Lending, which is increasingly popular and provides local companies and people with different ways to obtain funding without depending on foreign investment. Therefore, when both effects are balanced and offset each other, the net impact becomes insignificant.

5.1.3 Research Question 3

In evaluating the relationship between FDI and macroeconomic performance, the results vary across different indicators but consistently show that FDI explains only a minimal portion of the variation in these outcomes. This indicates that while FDI may have some influence, its direct impact on macroeconomic performance is generally limited. The reason behind this is largely due to the FDI tends to concentrate in specific sectors, which are often well-developed. Therefore, the benefits of FDI cannot be widespread across the whole economy, which further leads to a limited impact and an insignificant effect on specific economic performance.

Based on the regression results in Section 4.4, FDI is positively significant to both HFCE and GFCF, which is consistent with the theoretical findings. In general, besides direct capital injections in specific projects, FDI also promotes technology transfer and efficiency gains that further modernize and enhance sectors and increase productivity. This, in turn, encourages local innovation, attracts additional investment, and boosts capital formation, contributing directly to GFCF. Moreover, the increase in investment and capital injections stimulates market demand, leading to higher household consumption and spending, for example, through digital finance mechanisms. Additionally, by creating new investment opportunities, FDI helps bridge financing gaps in domestic projects, further reinforcing both capital formation and household consumption.

On the contrary, the insignificant result of FDI on GDP, Unemployment rate, and CO2 emission further reinforces the limitation of FDI in impacting the whole economy. Specifically, the insignificant result for GDP growth is likely due to the benefits of FDI being highly dependent on a country's absorptive capacity, particularly its financial depth, institutional quality, sectoral allocation, and supportive economic and policy environments. The wide differences among countries may also create a cancel-out effect, where the significant impact observed in some economies is offset by weak or negligible effects in others. For instance, in countries with low economic freedom, FDI may contribute little to no economic growth.

Furthermore, the insignificant result of FDI on the unemployment rate is reasonable because FDI-driven job creation is highly conditional and tends to favor specific sectors, such as manufacturing, technology, and high-value services. Foreign firms typically demand skilled labor to ensure productivity and meet project requirements. Therefore, the combination of sectoral concentration and limited opportunities for low-skilled workers can further widen income inequality and prevent a broad reduction in unemployment. Consequently, FDI does not translate into substantial reductions in overall unemployment.

Similar to the insignificant effect of FDI on CO_2 emissions, FDI is often linked to short-term profit-oriented projects and tends to be concentrated in sectors that are not highly polluting, such as services, technology, and finance (Bermejo Carbonell & Werner, 2018; Uddin et al., 2024). As a result, its overall impact on CO_2 emissions is limited. In addition, globally oriented supply chains, particularly in manufacturing and logistics, often prioritize cost efficiency over sustainability, potentially leading to negative environmental effects. Therefore, even though FDI can introduce modern, energy-efficient, and environmentally friendly technologies, the focus on short-term returns may reduce the observable significance of its effect on emissions.

5.1.4 Research Question 4

The regression results discussed in Section 4.5 indicate that FinTech development has only a limited impact on short-term economic performance. Among the FinTech indicators, only FinTech startups and BankTrans show a significant effect on the unemployment rate, although the results are somewhat contradictory.

Specifically, the positive effect of FinTech startups on the unemployment rate suggests that an increase in the number of startups is associated with higher unemployment. Although this result appears to contradict the theoretical expectations, it is consistent with the technological nature of FinTech startups. FinTech startups often introduce automation and efficiency through technology transfer, which can eliminate traditional roles, reduce costs, while maintaining or even enhancing overall efficiency and productivity (Liu & Chu, 2024). Routine positions, such as data entry and clerical tasks, are particularly vulnerable to being replaced by automated processes, leading to a temporary increase in unemployment in affected sectors (An et al., 2025; Kostov et al., 2025).

In contrast, BankTrans has a negative and significant effect on the unemployment rate, suggesting that higher levels of mobile and banking transactions are associated with lower unemployment. This indicates that when more people have access to mobile banking and digital transactions, economic activity is stimulated, which further encourages entrepreneurship and job creation. In detail, the greater access to banking transactions will expand financial inclusion, providing individuals and businesses with loans, credit, and working capital (Al-Smadi & Al-Smadi, 2024). With improved financial access, economic activity is further promoted, creating additional employment opportunities and establishing a reinforcing cycle between financial inclusion, increased economic activity, and job creation (Choudhary et al., 2025; Demir et al., 2022).

On the contrary, the effect of FinTech development is insignificant for other aspects of economic performance, including GDP growth, HFCE, GFCF, and CO_2 emissions. This insignificance can largely be attributed to the fact that FinTech development is still in its early stages, with relatively small sectoral size and limited penetration. As a result, FinTech activities are not yet substantial enough to influence broader economic performance significantly. At this stage, FinTech development primarily influences micro-level efficiency rather than macro-level economic aggregates. Specifically, FinTech advancements, including increased Internet access, mobile usage, and digital transaction activities, can enhance convenience, speed, and accessibility for individuals and firms. However, these micro-level improvements do not immediately translate into aggregate consumption (HFCE) or large-scale capital investment (GFCF). This suggests that the impact of FinTech on broader economic indicators may require a longer period to accumulate and become significant. Similar to the effect on CO_2 emissions, the focus of the FinTech sector is mainly on digital services, finance, and technology, which inherently produce minimal emissions compared to heavy industry (Satyanand, 2021; Zhang et al., 2024). Therefore, changes in FinTech indicators do not significantly affect CO_2 emissions, as the effect size is relatively small.

At the same time, there is also a notable but insignificant mediating effect of FDI on the relationship. As mentioned, FinTech is still in its early stages of development, with rapid growth occurring only in recent years. Moreover, FDI's impact on macroeconomic performance remains limited, as its benefits are highly conditional and depend on a country's absorptive capacity, including institutional quality, sectoral allocation, and government policies and frameworks. Therefore, the insignificant mediating effect of FDI is reasonable. Although the mediating effect is insignificant, FDI remains an important mediator between FinTech and economic performance to ensure theoretical completeness. Many theoretical frameworks suggest that the development of fintech can improve financial efficiency, enhance the accessibility of financial services, and reduce transaction costs. All of these factors influence a country's ability to attract foreign investment. Therefore, excluding foreign direct investment oversimplifies the relationship between fintech and economic performance, failing to reflect how the financial system actually operates.

5.1.5 Research Question 5

Based on the regression results in Section 4.6, the effect of FDI is not statistically significant for any of the individual SDGs achievements. These results suggest that the influence of FDI is not sufficiently widespread or strong enough to generate measurable improvements across the SDGs. For the composite SDG Index, the insignificant result is largely due to the concentration of FDI on the specific sectors like manufacturing, services, and extractive industries, which contradicts the target of SDGs that promote sustainable development and improvement in the areas of health, education, environmental quality, etc. Therefore, the contradiction of the primary focus means the benefits of FDI do not translate into significant results in the composite SDG performance.

Focusing on the economic dimension of the SDGs evaluated in this research, namely SDG 8 and SDG 9, the insignificant results can be explained by the same factors as the relationship between FDI and economic performance. However, SDG achievements reflect long-term structural outcomes, whereas economic performance indicators capture more immediate effects. In both cases, the limited impact of FDI is largely due to differences in countries' absorptive capacities, including institutional quality, financial depth, and sectoral allocation, which constrain the ability of FDI to generate widespread improvements.

Moreover, the effect of FDI on the social dimension of SDGs, including SDG 1 and SDG 10, is also not statistically significant. As discussed earlier, FDI is typically concentrated in specific sectors and in urban areas, and foreign firms tend to favour skilled labour to maintain efficiency and productivity. As a result, FDI does not effectively contribute to reducing inequalities and may even widen existing gaps between skilled and unskilled workers, limiting its impact on SDG 10. With such uneven distribution, poverty in rural areas remains largely unaddressed, as FDI does not directly reach or uplift these communities, which explains its insignificant effect on SDG 1. Furthermore, improving poverty reduction and inequality often requires strong social security systems, education, and inclusive policies, factors that foreign direct investment alone cannot provide. Therefore, these results further suggest that FDI does not exert a direct or broad impact on the social dimensions of the SDGs.

Similarly, the insignificant effect of FDI on the environmental dimension of the SDGs, represented by SDG 13 in this study, can largely be explained by the sectoral concentration of FDI. FDI often prioritizes short-term gains in specific sectors rather than sustainability. Consequently, this creates a potential conflict in decision-making, where firms may choose cost-reducing strategies instead of environmentally friendly practices. Therefore, FDI cannot directly contribute to environmental improvement and may even generate negative effects, which aligns with the consistently insignificant findings for both short-term CO_2 emissions and the long-term achievement of SDG 13. Additionally, environmental outcomes depend heavily on a country's regulatory framework. Even when FDI introduces modern and cleaner technologies, their effective adoption and integration into local sustainability efforts require strong environmental governance and supportive policies. Without these conditions, the potential environmental benefits of FDI remain limited, reinforcing the overall insignificant relationship observed.

5.1.6 Research Question 6

Based on the regression results in Section 4.5, FinTech development has a significant effect on most SDG achievements, except for SDG 13. This indicates that FinTech has a limited impact on environmental outcomes, both in the short term through CO_2 emissions and in the long term through climate action. In addition to the sectoral focus of FinTech activities and investments, negative externalities also contribute to this insignificant effect. Although FinTech can introduce cleaner and more modern technologies, some FinTech activities, for example, the high energy consumption of cryptocurrency mining, may generate adverse environmental effects. These conflicting impacts suggest that FinTech does not exert a positive and significant influence on climate action. Moreover, environmental improvement depends heavily on effective government regulation and integration with sustainability policies. As a result, FinTech development alone cannot substantially influence environmental outcomes, given its relatively small scale and primary focus on financial and transaction-related activities.

Although most SDGs show significant positive results, FinTech startups are an exception, as they exhibit a negative effect on SDG 8 and SDG 9, which contrasts with the effects of other FinTech indicators. Focusing on SDG 8, which promotes decent work and economic growth, the negative impact of fintech startups can largely be explained by the fact that the rapid expansion of fintech companies has intensified competition, particularly for traditional financial institutions that still rely on conventional financial solutions. This heightened competition can lead to restructuring and job displacement in traditional sectors, thereby weakening the positive contribution of FinTech to employment and economic growth. Similarly, the negative effect of FinTech startups on SDG 9 aligns with institutional theory, which suggests that FinTech adoption may be driven more by legitimacy than by efficiency. In this context, adoption occurs due to normative and cultural–cognitive pressures rather than real productivity improvements. As a result, the infrastructure associated with FinTech expansion may not translate into meaningful or effective improvements in industrial development and innovation capacity across countries.

Moreover, the significant effects observed for SDG 1, SDG 8, SDG 9, and SDG 10 indicate that FinTech development primarily influences sustainable development through long-term structural channels rather than immediate economic outcomes. The significance of the Internet, BankTrans, and Mobile suggests that FinTech operates through a cumulative mechanism that enhances financial inclusion and economic participation over time. Specifically, improved access to affordable and efficient financial services reduces financial exclusion, contributing to SDG 10 by narrowing inequality gaps. Increased financial inclusion also facilitates entrepreneurship and productive activities, which support decent work and economic growth under SDG 8. Over time, innovation-driven employment opportunities generated by FinTech development can raise income levels and contribute to poverty reduction under SDG 1. In addition, technological advancement within the FinTech sector strengthens digital and financial infrastructure, thereby supporting progress toward SDG 9.

Overall, it is notable that among the FinTech indicators, Internet penetration consistently exhibits a significant effect across almost all SDG achievements. This highlights the critical role of Internet access in enabling FinTech development, which in turn can influence sustainable development outcomes. The Internet serves as the foundational technology for FinTech, providing the primary channels for accessing digital financial services. It also functions as essential infrastructure for various FinTech applications, including mobile transactions, blockchain, and machine learning-based services, which can effectively support the functioning and expansion of the entire FinTech ecosystem.

In addition, the results of RQ5 indicate that income level moderates the relationship between internet or fintech development and the achievement of SDGs, except for the startup indicator. For SDG 8 and SDG 10, the moderating effect is positive, suggesting that high-income countries with more robust financial infrastructure, higher digital literacy, and wider technology adoption are able to more effectively utilize fintech to promote economic growth, job creation, and financial inclusion. In contrast, for SDG 1, the moderating effect is negative, which may reflect a ceiling effect. It means that poverty rates are already low in high-income countries, so the additional benefits of internet access are smaller (Choudhary et al., 2025), while in low-income countries, internet access significantly enhances financial inclusion and economic opportunity, resulting in greater poverty reduction benefits. These patterns suggest that the impact of technology on the SDGs is context-dependent and influenced by national income and development levels.

5.2 Implications of the Research

Combining all the research results, both significant and insignificant findings offer important contributions and implications, particularly for governments, traditional financial institutions, and FinTech firms. This study provides practical guidance for decision-making based on the results, helping stakeholders to design strategies that support effective FinTech development. In addition, the findings contribute to theoretical advancements by enhancing our understanding of the mechanisms through which FinTech influences economic performance and sustainable development outcomes.

Firstly, given the strong significance of FinTech development for sustainable growth, governments should implement tailored regulatory frameworks for FinTech companies rather than adopt a one-size-fits-all approach and include the consideration of market acceptance, the maturity of the financial sector, and country-specific policies. In this way, FinTech development can grow effectively while promoting financial stability, fostering innovation, and maximizing its contribution to economic growth and sustainable development goals. In addition, governments should provide incentives for FinTech startups and firms to encourage the growth of the sector, reduce financial gaps, and improve economic performance and equality. Although the immediate impact might not be strong, these measures are expected to generate positive effects in the long run.

At the same time, even though the results show that FDI is not significant for most economic performance indicators and SDGs, governments should continue to encourage and support FDI. This is because the benefits of FDI may require a better framework to be realized, such as improved regulation, sectoral allocation, and institutional capacity. Moreover, the time horizon of this study may be too short to capture the long-term effects of FDI. With appropriate policies and supportive environments, FDI can eventually contribute to capital formation, technology transfer, and broader economic development, complementing the impact of FinTech development.

In addition, traditional financial firms should recognize the growing trend of FinTech, which is gradually replacing conventional financial solutions. To strengthen their position and remain competitive, they should adopt strategies to address digital disruption. For example, traditional banks can integrate FinTech solutions into their existing operations to enhance efficiency and automation by leveraging data analytics and AI tools. This integration can improve customer satisfaction by providing faster, more secure, and more convenient services.

Similarly, FinTech startups and firms should identify growth opportunities and expand their current operations, especially given the significant impact of FinTech on sustainable development goals. At the same time, since the effect of the FinTech sector on FDI is still not significant, there remains potential for new opportunities in attracting foreign investment and forming strategic partnerships that could further strengthen the sector and its contribution to the broader economy.

5.3 Limitations

Throughout this research, several limitations have been identified that constrain a more complete and in-depth understanding of the results. The first limitation relates to the infant stage of FinTech development. Although FinTech has experienced rapid growth in recent years, particularly during the peak of the COVID-19 pandemic, FinTech development in many low and lower-middle-income countries remains underdeveloped and at a very early stage. In this study, the availability of FinTech indicators is highly uneven across countries. For example, for the FinTech metric BankTrans, only 65 countries have complete data for the period from 2017 to 2023. As a result, only one country in the low-income category could be included in the analysis with complete secondary data. This data limitation may introduce potential bias, reduce observable variation across income groups, and consequently limit the generalizability of the results.

Moreover, the availability of comprehensive annual data for measuring FinTech development remains limited. In this study, the FinTech indicators used, such as mobile and banking transactions and mobile cellular subscriptions, may not fully reflect FinTech infrastructure, innovation, or the overall ecosystem. This is because these measures have been present in the market for a long time and may not capture newer forms of FinTech development, such as blockchain-based services. Specifically, within the World Bank DataBank, the most relevant FinTech-related metrics, such as mobile money adoption and digital account ownership, are primarily available for higher-income economies and are often reported only once every three years. As a result, these indicators are unable to accurately capture both the immediate and long-term effects of FinTech development in a panel-data framework. Consequently, there remains a lack of more comprehensive and high-frequency metrics, such as measures of digital financial services usage, equity crowdfunding activity, or peer-to-peer lending adoption.

Furthermore, the availability of social indicators remains limited, which poses a constraint on assessing the broader social impact of FinTech development. In this study, the Gini coefficient is incomplete, as it is only available for certain years and has a limited number of countries. This limitation reduces the ability to assess inequality accurately and constrains the scope of panel analysis. Due to the lack of suitable short-term proxies linking FinTech development to long-term SDG 10 achievements, the study's ability to capture dynamic and transitional effects is further restricted.

5.4 Recommendations for Future Research

To have a deeper understanding of the direct impact of FinTech development, future research should replicate this study using more comprehensive and precise metrics that better reflect FinTech infrastructure and development across countries. With the rapid growth of FinTech globally, metrics capturing emerging technologies, such as blockchain adoption, AI-driven financial services, and IoT-enabled financial platforms, are expected to become increasingly available. In addition, existing data are likely to expand to annual coverage in the future. Once this data are available, it is highly recommended to redo this study to provide a more complete analysis of both the direct and indirect impacts of FinTech on economic performance and SDGs, while reducing potential biases in the analysis.

Secondly, future research should extend the study period to cover a longer time frame, for example from 2017 to 2028. This would help mitigate the effects of exceptional events, such as the COVID-19 pandemic, which affected 2 out of 7 years in the current study, accounting for 28.57% of the overall period. A longer time frame would allow for more robust panel-data analysis and provide better insights into long-term trends and causal relationships, capturing the sustained effects of FinTech development.

Finally, as noted in the limitations, socioeconomic indicators are currently largely unavailable, which constrains the analysis of social outcomes. However, their impact is highly important, as reflected in the significant results for SDG 10. Therefore, future studies should incorporate more complete and frequent data on inequalities and other social indicators to strengthen the assessment of FinTech's impact on social outcomes, particularly regarding long-term contributions to financial inclusion and equitable economic growth.

5.5 Chapter Summary

In conclusion, several key findings have been identified. First, FinTech development shows significant differences across income levels. In lower-income economies, common structural and market limitations constrain the growth of the FinTech industry. Therefore, development remains in the infant stage, especially in low-income economies, particularly in terms of Startup, Internet, and BankTrans indicators.

Although the relationship between FinTech and FDI is not statistically significant, this is largely because FinTech development is still at an early stage. Overall, the effect of FDI on economic performance and SDG achievement is limited or insignificant, with significant results only for HFCE and GFCF. This further confirms that the impact of FDI is conditional, depending on the absorptive capacity of economies. Due to the complexity of FDI, its attraction and implementation may be limited, requiring cooperation and alignment of government policy, institutional quality, and other factors. Taken together, these results confirm that the effect of FDI is mainly conditional, which explains the insignificant findings.

Moreover, the effect of FinTech on economic performance is more direct, but limited, being significant only for unemployment. Specifically, the results suggest that access to mobile services and banking transactions creates more opportunities for online businesses, such as e-commerce, which stimulates economic activity and generates job opportunities, thereby reducing unemployment. However, it is also notable that FinTech startups may increase competition with traditional financial institutions, potentially crowding them out, while automation may eliminate routine roles, which could increase unemployment in certain sectors.

Notably, the most significant finding is that FinTech development is highly significant for SDG achievement, representing a long-term effect. However, there are conflicting results among FinTech indicators. FinTech startups may crowd out traditional financial institutions, but access to Internet, BankTrans, and mobile services produces positive results, promoting financial inclusion, entrepreneurship, stimulating economic activity, and helping reduce inequalities.

Combining these results provides important insights for governments, traditional financial institutions, and FinTech firms. Given the significant effect of FinTech on SDGs, governments should provide incentives and develop a tailored regulatory framework to foster sector growth and maximize its contribution to long-term sustainable development. Traditional financial institutions should recognize the growth and significance of FinTech companies and take strategies to face competition in the market. For FinTech firms, proper adoption strategies are important to avoid simply following market trends and to enhance efficiency and competitiveness.

Finally, this research has several limitations, particularly regarding data availability for FinTech development metrics and social indicators like the Gini coefficient, which limits the depth and completeness of the study. Nonetheless, this research provides initial insights, and future studies should redo the topic when more appropriate data and metrics are available. Additionally, the research period should be extended to capture exceptional events, such as COVID-19, to reduce potential bias. Extending the period is strongly recommended for future research.

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