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Technology-Led Sustainable Development Under Economic Policy Uncertainty: Cross-Country Evidence from Fintech Innovation and Digital Transformation

by

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CERTIFICATE OF APPROVAL

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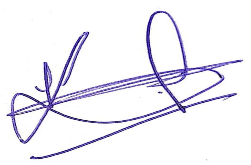

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(Kainat Shahbaz)

Abstract

As developing economies increasingly position FinTech innovation and digital transformation as engines of sustainable development, the institutional conditions under which these technologies deliver returns remain poorly understood. This study examines the effects of digital transformation and FinTech innovation on the Human Development Index (HDI) and Environmental Performance Index (EPI), and tests whether Economic Policy Uncertainty (EPU) operationalized through a novel time-weighted formulation moderates these relationships across 45 developing and emerging economies, 2010–2022, using a four-estimator framework (System GMM, DOLS, Fixed Effects with Driscoll-Kraay standard errors, and FGLS). Digital transformation and FinTech innovation both significantly improve HDI, with EPU dampening but not reversing these gains. Neither technology channel significantly affects EPI directly, consistent with the Environmental Kuznets Curve.Instead, EPU alone emerges as the dominant determinant of environmental performance across all estimators, substantially exceeding the influence of income, geopolitical risk, or either technology channel. These findings show that technology's sustainable development returns are institutionally conditional, not universal, and markedly weaker environmentally than developmentally. Policymakers and development institutions should treat macroeconomic and regulatory credibility as a precondition for realizing digital investment's sustainable development potential, particularly in high-uncertainty economies.

Keywords: Digital Transformation, FinTech Innovation, Sustainable Development, Economic Policy Uncertainty, Emerging Economies.

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Abbreviations

ADF	Augmented Dickey-Fuller Test
DigiTrans	Digital Transformation (Index)
DK SE	Driscoll-Kraay Standard Errors
DOLS	Dynamic Ordinary Least Squares
DP	Digital Payments
DWH	Durbin-Wu-Hausman Test
EKC	Environmental Kuznets Curve
EPI	Environmental Performance Index
EPU	Economic Policy Uncertainty
EPU_tw	Time-Weighted Economic Policy Uncertainty
FE	Fixed Effects
FGLS	Feasible Generalized Least Squares
GDPPC	Gross Domestic Product Per Capita
GMM	Generalized Method of Moments
GPRI	Geopolitical Risk Index
HDI	Human Development Index
IMF FAS	IMF Financial Access Survey
MICE	Multiple Imputation by Chained Equations
PCA	Principal Component Analysis
PMM	Predictive Mean Matching
SDG	Sustainable Development Goal
VIF	Variance Inflation Factor

Chapter 1

Introduction

1.1 Background of the Study

Ten years after investing in digital infrastructure and financial technology, two countries can be at vastly different levels of sustainable development, not because of the technology, but because of the certainty of their policy environments. This contrast is not an abstract one. This thesis is motivated by the central empirical fact. The only thing that remains unanswered and under question is whether technology can drive sustainable development or not, when developing countries are being encouraged to adopt FinTech innovation and digital transformation as a means to achieve sustainable development. The question is explored in this thesis.

There have been two forces in the 21st century that have been transforming at the same time. The first is the global commitment to sustainable development; the idea that sustainable development, as recognized in the United Nations Sustainable Development Goals and expressed since the Brundtland Commission's 1987 report, requires the simultaneous progress of human welfare, economic opportunity, and environmental sustainability. The second is the swift spread of digital and financial technologies, ranging from infrastructure for the internet to mobile connectivity, to digital payment systems, that have transformed the way economies work and how households and firms access resources. The intellectual and practical challenge that emerges at the crossroads of these two is both compelling and meaningful: can

FinTech innovation and digital transformation be a true catalyst for sustainable development and when, and under what institutional conditions?

This study investigates this question by conducting an empirical cross-country analysis of 45 developing and emerging economies between 2010 and 2022, based on two complementary outcome measures: the Human Development Index (HDI) which captures health, education, and income outcomes, and the Environmental Performance Index (EPI) which measures ecological performance based on 32 environmental indicators.

Digital payment adoption is the vehicle for FinTech innovation, and a composite infrastructure index is the vehicle for digital transformation, so their impact on sustainable development can be measured together and not just by a single undifferentiated technology indicator.

At the heart of this design is the consideration of these effects as contingent rather than constant: Economic Policy Uncertainty is treated as a moderating variable, and is measured as a time-weighted index that reflects the cumulative impact of chronic policy uncertainty, not its current level.

Sustainable development is development that satisfies the needs of the present generation without harming the capacity of future generations to satisfy their own needs (Brundtland Commission, 1987). This definition had sweeping ramifications for the measurement of progress. The post-war measure of national success, Gross Domestic Product, measures total income, but not health, education, freedom or environmental sustainability. The Human Development Index was a direct response to this limitation, first introduced by the United Nations Development Programme in 1990 and based on the Capabilities Approach, which was developed by Amartya Sen (Haq, 1990; Ranis et al., 2000) and which views development as an increase in the range of possibilities for people to be and do. The Environmental Performance Index (EPI), which is produced every two years by the Center for Environmental Law and Policy at Yale University, focuses on the ecological dimension deliberately omitted from HDI, and comes with 32 performance indicators and 11 categories, giving a broad picture of a country's relationship with its natural environment (Yale Center for Environmental Law and Policy, 2022).

These two indices are the most comprehensive available publicly available measure of sustainable development, which is why they are used as the two outcome variables in this study, instead of the one indicator proxies used in much of the previous literature.

This multidimensional understanding of progress was translated into 17 Sustainable Development Goals in the 2030 Agenda for Sustainable Development adopted by the United Nations in September 2015. The SDGs that are relevant to this study are SDG 1 (No Poverty), SDG 3 (Good Health and Well-Being), SDG 4 (Quality Education), SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation and Infrastructure), SDG 10 (Reduced Inequalities), and SDG 13 (Climate Action).

The adoption of digital payment and overall digital transformation are now widely known as cross-cutting enablers of these objectives,they increase financial access (SDG 1, SDG 10), decrease the cost of providing health and education services (SDG 3, SDG 4), boost productivity and inclusive growth (SDG 8), create technological infrastructure (SDG 9), and can help to achieve resource-efficient production patterns that lower ecological footprints (SDG 13). Thus, the empirical question this study is addressing whether these enabling effects are dependent on the quality of the institutional environment is not only an academic one but also one of practical importance for the implementation of the 2030 Agenda in developing and emerging economies.

This measurement framework is needed because both sustainability indices have been on a downward trend over the past few years. Perhaps the most dramatic policy uncertainty shock during the period studied was the COVID-19 pandemic, which led to a wide range of policy reversals, emergency fiscal interventions, and monetary policy measures that are as unpredictable as the kind the time-weighted EPU formulation of this study aims to capture. The results were devastating, United Nations Development Programme (2022) reported that the global HDI hit a record low in the last two years since the index was launched in 1990, wiping out about five years of development progress in just two years. At the same time, global CO_2 emissions, which had dipped slightly during the economic slowdown in 2020 due to the pandemic, increased to a record 36.5 billion tons in 2021, highlighting the continued absence of fundamental change in the structural causes of environmental degradation (Yale Center for Environmental Law and Policy, 2022). These twin reversals are not just numbers, but a sign that the institutional environment is not a silent partner of sustainable development but a key factor in whether investments, technologies and financial innovations that are supposed to propel development actually achieve their potential.

The gains in the 30 years leading up to the onset of the pandemic had been impressive yet fragile. The percentage of the global population living in extreme poverty (those with incomes of less than USD 2.15 per day in 2017 PPP) dropped from around 36 percent in 1990 to less than 9 percent in 2019, one of the greatest successes in economic history. Life expectancy has increased from 65 years in 1990 to more than 73 years in 2019. Near universal access to primary education was achieved in most areas.

However, as the events of 2020 and 2021 have shown, these advances have also been unequal, environmentally expensive, and institutionally fragile. The countries with less developed fiscal systems, poorer health care systems, and greater reliance on informal labor markets, the developing economies that make up this study's sample, were hardest hit and hit the hardest. The Covid-19 pandemic has not only made the SD challenge more urgent than ever, it has also brought the institutional shortcomings that limit the SD response to the forefront.

In this context of two crises, human development and environmental performance, financial technology has become a key component of the global development policy agenda. The idea of FinTech as a development mechanism is rooted in a structural issue that has been well documented: the continued underrepresentation of large portions of the population of developing countries in formal financial systems. As of 2021, the World Bank Global Findex Database estimated that around 1.4 billion adults had no access to any form of formal savings or transaction account (World Bank, 2022). The effects of this exclusion multiply in all aspects of sustainable development. The absence of formal saving arrangements prevents households from creating buffers to cope with income shocks, smoothing consumption through shocks, and investing in education and health are all direct drivers of HDI. The absence of payment systems makes the costs of commonplace commercial transactions high and income is diverted from productive and welfare-augmenting uses. Financial exclusion is not only a financial issue it is a human development issue, an environmental issue, a growth issue, because the people who are most vulnerable to financial exclusion are least able to invest in sustainable practices, efficient technologies and adaptive investments that are needed for long-run development.

The empirical literature now provides a growing body of evidence on the link between FinTech and SDGs. The findings from the cross-country evidence are recent and confirm that fintech diffusion and digital financial inclusion boost the accessibility of financial services and speeds up the adoption of productivity-enhancing technologies by lowering information asymmetry and transaction costs, directly contributing to multiple SDG dimensions such as poverty reduction, inequality reduction, economic growth and infrastructure development (Banna et al., 2022; Choudhary and Thenmozhi, 2024; Daud and Ahmad, 2023).

Importantly, this literature also reveals that the relationship is two-way: the development and progress of fintech can reinforce SDG progress, and the progress of SDG can reinforce the development and progress of fintech, in the presence of a sufficiently stable institutional environment that can sustain these virtuous cycles of inclusion and development.

The mechanisms by which FinTech can tackle financial exclusion are qualitatively distinct from the mechanisms by which traditional financial deepening can tackle financial exclusion. Traditional banking expansion demands physical infrastructure i-e branch networks, ATMs, and the legal and regulatory framework of chartered deposit-taking institutions whose up-front costs prevent their economic viability in reaching low-income, geographically dispersed, or informally employed populations. Mobile money platforms, on the other hand, use the existing telecom infrastructure to provide financial services at near zero marginal cost to mobile phone owners. The model was most clearly demonstrated by the M-PESA platform, launched in 2007 in Kenya, which within ten years of its launch had facilitated transactions that exceeded 40 per cent of Kenya's GDP annually, enrolled tens of millions of previously unbanked users, and had measurable impacts on household consumption, poverty reduction, and women's economic empowerment (Jack and Suri, 2014; Suri and Jack, 2016). Since then, other platforms have been rolled out in Sub-Saharan Africa, South Asia and Latin America. As of 2021, mobile money transactions had reached over 1 trillion, with 866 million registered mobile money accounts across 90 countries, making it the largest documented formal financial access growth in economic history (GSMA, 2022). This financial inclusion channel is operationalized in this study by measuring digital payment adoption, defined as the value of mobile payment transactions as a share of GDP, which reflects the economic depth of digital payment penetration in each economy, rather than just the presence of digital payment accounts.

The mechanism through which digital payment adoption drives sustainable development operates across multiple reinforcing channels. At the household level, mobile money reduces the cost and risk of storing and transferring value, enabling households to build savings buffers that smooth consumption across income shocks , a direct contributor to the health and income dimensions of HDI (Jack and Suri, 2014).

At the firm level, digital payment infrastructure reduces transaction costs for small enterprises that would otherwise rely on costly informal payment mechanisms, freeing resources for productive investment and enabling access to a broader customer base (Daud and Ahmad, 2023). At the government level, digital payment systems enable more efficient and corruption-resistant delivery of social transfers, subsidies, and public wages with documented effects on the reach and impact of social protection programs across developing economies (World Bank, 2022). Each of these channels represents a direct pathway from FinTech adoption to the income, health, and education improvements that constitute HDI a pathway that is activated at scale only when the regulatory and institutional environment is stable enough for households and firms to trust and invest in the technology.

The environmental dimension of FinTech's development impact is less direct but equally significant. Digital financial services can lower the resource intensity of economic transactions by substituting paper-based and physically intermediated processes with digital equivalents reducing the carbon footprint associated with physical branch networks, cash transportation, and paper documentation. More importantly, expanded financial access enables small producers and households to invest in energy-efficient technologies, renewable energy systems, and sustainable agricultural practices that would otherwise be inaccessible due to capital constraints (Banna et al., 2022). The empirical evidence on this environmental channel is more mixed than the human development story in part because the income growth that FinTech enables can also increase consumption of environmentally intensive goods but the balance of recent cross-country evidence suggests a positive net effect on environmental performance, particularly in contexts where expanded financial access accelerates the adoption of clean technology rather than merely increasing consumption of carbon-intensive alternatives.

Digital transformation is the second major independent variable in this study, operating through a broader and more pervasive channel than any specific FinTech application. The systematic integration of digital technologies , mobile connectivity, internet infrastructure, high-speed broadband, and ICT-enabled services into economic and social life reshapes productivity across all sectors simultaneously. The theoretical foundation for this mechanism is provided by Romer (1990) endogenous growth framework, which identifies technological knowledge as the primary engine of long-run growth, and by the applied digital development literature that has operationalized this insight across developing economy contexts (Balsalobre-Lorente et al., 2025; Sayari et al., 2025).

According to the UNCTAD (2025), the digital economy is expanding at an annual rate of 10 to 12 percent, outpacing global GDP growth and accounting for a rising share of value creation worldwide yet less than 15 percent of cross-border digital sector investments involve companies from developing countries, underscoring the structural inequality in digital transformation's global diffusion (UNCTAD, 2025).

The sector-level mechanisms through which digital transformation drives sustainable development are well-established in the empirical literature. In agriculture, digital platforms reduce information asymmetries between producers and markets, enabling farmers to receive real-time price data and agronomic advice through mobile devices with documented effects on rural incomes and food security across developing regions (Wang et al., 2025). In healthcare, telemedicine and remote diagnostics extend effective care beyond the reach of physical facilities, improving the health dimension of HDI at reduced fiscal cost.

In education, internet connectivity enables distance learning that is particularly transformative in regions where qualified teachers and quality materials are scarce.

At the macroeconomic level, digitalization enables a structural shift toward service-based industries whose resource intensity is substantially lower than manufacturing a transition whose environmental benefits have been documented across a range of developing economy contexts (Manu and Asongu, 2025; Balsalobre-Lorente et al., 2025).

Importantly, these forces are best understood as complementary rather than interchangeable: digital transformation creates the enabling infrastructure, while FinTech delivers the financial access applications that translate that infrastructure into measurable development gains.

A particularly significant channel through which digital transformation affects environmental performance is what the literature terms green digitalization: the use of digital technologies to actively monitor, manage, and reduce environmental impacts. Smart grid technologies reduce electricity waste.

Digital supply chain management systems optimize logistics routes and reduce fuel consumption. Remote sensing and satellite data enable real-time monitoring of deforestation, water quality, and air pollution.

These green digital applications represent a qualitatively new relationship between technology and the environment one in which digital tools are not merely incidentally cleaner than their analog equivalents but are actively deployed as instruments of environmental governance.

For developing economies that lack the physical monitoring infrastructure of advanced nations, these digital environmental management tools represent a potentially transformative shortcut to environmental performance improvements that would otherwise require decades of institutional and infrastructural investment.

The relationship between digital transformation and environmental performance is, however, more complex than the human development story and deserves explicit acknowledgment. Digital infrastructure itself consumes substantial electricity, and the income growth that digital transformation generates increases demand for goods and services whose production creates environmental costs.

The Environmental Kuznets Curve hypothesis, first formalized by Grossman and Krueger (1995), predicts that environmental degradation initially worsens with income growth before eventually improving as higher incomes generate demand for cleaner technologies and more effective environmental regulation.

Since the majority of economies in this study's sample occupy the rising portion of the Kuznets curve, the income-enhancing effects of digital transformation may, in the short to medium run, exert upward pressure on ecological footprints even while improving human development.

However, recent cross-country evidence increasingly finds that the net effect of digital transformation on environmental performance is positive even in developing country samples when estimation adequately controls for income levels and country-specific heterogeneity (Sayari et al., 2025; Manu and Asongu, 2025; Nguyen et al., 2020). This net positive result reflects the dominance of efficiency and governance channels smart resource management, digital environmental monitoring, and supply chain optimization over the energy demand costs of digital infrastructure. The digital divide is the systematic inequality in digital access and capability across countries and it introduces a critical qualification to the optimistic narrative of digital transformation as a universal development driver. UNCTAD (2025) reports that greenfield investment in digital services in developing countries rose from USD 6 billion in 2020 to USD 37 billion in 2024, yet nearly 80 percent of this investment went to just 10 countries leaving the majority of developing economies with a digital infrastructure investment gap estimated at USD 1.6 trillion.

This concentration means that the sustainable development benefits of digital transformation are not uniformly distributed across the developing world,they accrue disproportionately to those economies that can attract and sustain digital investment, which in turn is partly a function of the institutional environment's stability and predictability. This observation provides one of the core theoretical motivations for this study's moderation analysis: whether the institutional environment, proxied by EPU, systematically conditions the sustainable development returns to both FinTech and digital transformation.

The thread that ties this study's narrative together is Economic Policy Uncertainty as a moderating force and it is arguably the single most important analytical contribution of this research relative to the existing literature. The Baker et al. (2016) EPU index, constructed from the frequency of newspaper coverage of economic policy uncertainty-related terms combined with measures of forecaster disagreement about government fiscal variables, provides a time-varying measure of policy instability that is conceptually distinct from general macroeconomic volatility.

The foundational empirical finding of Baker et al. (2016) that increases in EPU are followed by significant and persistent declines in investment, employment, and output growth has been replicated across dozens of country and sector contexts over the past decade.

The theoretical mechanism is provided by real options theory: when the future policy environment is unclear, the option value of deferring irreversible, capital-intensive investment is positive, and rational actors will wait for clarity before committing resources (Dixit and Pindyck, 1994; Bloom, 2009).

Digital infrastructure projects and FinTech platform deployments are precisely the types of investment most sensitive to this dynamic their lack of asset reversibility, large capital requirements, and returns that are fundamentally contingent on stable regulatory frameworks governing digital financial services, data protection, and telecommunications licensing make them acutely vulnerable to the investment-suppressing effects of sustained policy uncertainty.

The EPU-investment relationship takes on a distinctive character in developing and emerging economy contexts that distinguishes it from the well-documented dynamics in advanced economies. In developed countries, EPU typically operates against a backdrop of strong institutional foundations i-e independent central banks, rule of law, credible regulatory agencies that limit the translation of policy uncertainty into investment deterrence. In developing economies, these institutional buffers are weaker, meaning that EPU shocks translate more directly and durably into investment contractions. Furthermore, EPU in developing economies is more likely to be accompanied by currency volatility, sovereign risk repricing, and capital flight compounding effects that amplify the direct investment-deterrence mechanism.

The EPU-sustainable development nexus therefore operates differently across the income distribution in ways that the existing literature, which draws primarily on advanced economy data, has not adequately captured. This study's sample of 45 developing and emerging economies is specifically designed to illuminate this underexplored institutional dimension.

Recent evidence from international investment data confirms this EPU mechanism at scale. The UNCTAD Trade and Development Foresights 2025 report documents that trade policy uncertainty, now at historic highs, is weighing heavily on business confidence and long-term planning with manufacturers and investors delaying decisions, reassessing supply chain strategies, and stepping up risk management efforts (UNCTAD, 2025).

Critically, this uncertainty-driven investment caution is directly threatening progress toward the Sustainable Development Goals: in 2024, investment in SDG-aligned sectors fell sharply, with project finance in renewable energy declining by 16 percent precisely the kind of clean technology investment that EPU's real options mechanism predicts will be most severely curtailed (UNCTAD, 2025). This contemporary evidence corroborates the theoretical predictions of this study's moderation framework and underscores the policy urgency of understanding how EPU moderates the sustainable development returns to digital investment.

Critically, long-horizon investments are not derailed by brief spikes in uncertainty they are derailed by the gradual accumulation of sustained policy instability. A country that experiences a single-year EPU shock recovers its investment climate relatively quickly once the shock dissipates. A country that has endured a decade of persistently elevated EPU develops an investor psychology and a planning horizon that is structurally different: one in which the default response to uncertainty is not to wait and see, but to permanently discount the future and indefinitely defer commitment.

It is this compounding, structural damage to investment confidence distinct from any transient shock that the time-weighted EPU operationalization of this study is designed to measure. By weighting each period's EPU level by its temporal proximity and cumulative duration, the time-weighted formulation captures what a standard period-average EPU measure misses: that sustained policy uncertainty causes qualitatively different and more persistent investment and development damage than episodic uncertainty of equal magnitude.

The time-weighted formulation of the EPU in this study explicitly weights the burden of policy uncertainty across a country's observation history, whereas the contemporaneous or period-average EPU measures found in the existing literature assume that a single year of high uncertainty is the same as a decade of high uncertainty. It is not just a conceptual distinction, but an empirical one as well: the fact that this measure is consistently significant across four estimators that have very different identifying assumptions (System GMM, DOLS, Fixed Effects with Driscoll-Kraay standard errors, and FGLS) indicates that the time-weighting reflects a real, persistent institutional effect, not just a quirk of any one specification.

1.2 Theoretical Background

Why should digital transformation or FinTech adoption lead to improved human development and environmental outcomes in all countries and why should this link be contingent on the stability of a country's policy environment? The answers to these questions cannot be given by an empirical model alone, but also requires a theoretical account of the mechanism by which technology becomes development, and the conditions under which this mechanism can break down. This section develops that account. It starts by examining the concept of technological capacity and its ability to create productivity and welfare benefits, then moves to the channel through which financial technology is delivered to the unbanked population, and finally concludes with the rationale behind the core argument of this study: that policy uncertainty is not just a byproduct of technological investment, but a determinant of its returns. These arguments form the theoretical basis for the four hypotheses of this study.

1.2.1 Endogenous Growth Theory

The endogenous growth theory is the basis for the mechanism of digital transformation and sustainable development gains. In Solow (1956) neoclassical growth model, technological progress was considered an exogenous residual, a force that acts on the economy but is not included in the model, nor is its origin or its drivers explained. This is a radical departure from Romer (1990) endogenous growth framework, which redefines technology as a knowledge-enhancing process that is endogenous to the economic system and whose non-rival nature allows for increasing returns at the aggregate level, thus increasing the productivity of all other inputs as well.

This is not an incidental to the present study, but it is fundamental. Romer's framework assumes technological capacity is endogenous, meaning that the returns to digital transformation are endogenous as well, and are conditioned on the production, deployment and sustainability of the technology. In this reading, digital infrastructure is not a one-way input whose impact is automatic, but rather a productivity-enhancing force that requires institutional conditions that are compatible with it, and this study directly tests this by conditioning the returns of digital transformation on Economic Policy Uncertainty. It is in line with the Industry 5.0 paradigm, which explicitly defines the technological deployment as dependent on the institutional and societal readiness, and not the technological capability and its developmental payoff as being coextensive (Xu et al., 2021)

In this context, digital transformation is a generic productivity tool applicable to different sectors, such as precision agriculture, telemedicine, distance learning, and digitally optimized supply chains, which all share the same logic of knowledge spillovers and their benefits for welfare, measured by HDI, and resource efficiency, measured by EPI. This is the theoretical basis for Hypothesis 1: digital transformation positively and significantly impacts sustainable development.

1.2.2 The Financial Inclusion-Development Hypothesis

The Financial Inclusion-Development Hypothesis suggests that increased access to formal financial intermediation (savings, credit, payments) has measurable and lasting positive impacts on income stability, health investment, and educational attainment, and that these impacts are strongest for those who were previously under-served by formal financial systems. The mechanism is known at the household level: formal savings lower the volatility of household income, which forces poor households to withdraw children from school or delay medical treatment; access to credit allows productive investment; and a reliable payment system lowers transaction costs that disproportionately affect the poor (Levine, 2005; Demirguc-Kunt and Klapper, 2013).

FinTech is the main driver of this mechanism, solving the fixed-cost issue that makes it difficult and unprofitable to expand traditional banking in low-density, low-income areas. This study's operationalization of FinTech (digital payment transactions as a percentage of GDP) directly reflects this channel of financial inclusion, and is the theoretical basis for Hypothesis 2: FinTech innovation positively and significantly affects sustainable development.

1.2.3 Uncertainty-Investment Framework

The theoretical foundation for this study's main contribution, Economic Policy Uncertainty as a moderating force, is the Uncertainty-Investment Framework, which is rooted in the real options literature of Dixit and Pindyck (1994) and the empirical EPU methodology of Baker et al. (2016). Real options theory shows that investment decisions under uncertainty are asymmetric: if the future policy environment is uncertain, the value of waiting to make an irreversible, capital-intensive investment is positive, and rational investors will wait until they have enough information to make the investment decision (Dixit and Pindyck, 1994; Bloom, 2009).

Digital infrastructure projects and FinTech platform deployments meet all three of the conditions that digital infrastructure theory identifies as making a project highly sensitive to policy uncertainty: they are capital-intensive, largely irreversible once sunk, and the returns are dependent on stable policy environments for digital finance, data protection, and telecommunications licensing. The more EPU increases, the more uncertainty increases in all of these regulatory dimensions, and the theory suggests a systematic reduction in digital investment, which is the basis for both FinTech adoption and digital transformation. This mechanism of policy uncertainty dampening the investment that turns technological potential into sustainable development outcomes is what leads to Hypotheses 3 and 4: Economic Policy Uncertainty negatively moderates the relationship between digital transformation and sustainable development, and between FinTech innovation and sustainable development, respectively. This framework has special validity in the context of developing and emerging economies. In advanced economies, EPU generally takes place in the context of institutional buffers that reduce the impact of EPU on investment deterrence, such as independent central banks, rule of law, and credible regulatory agencies. The structural fragility of these buffers is reflected in the sample in this study, and therefore EPU shocks are more directly and persistently manifested in investment contraction, sometimes exacerbated by currency volatility and capital flight. The asymmetry is the theoretical foundation for the time-weighted EPU formulation developed in Section 3.2.3, which reflects the cumulative, not just the short-term impact of persistent policy volatility on long-term technological investment.

1.3 Research Gap

There is already a considerable body of work on how digital technology relates to sustainable development, but three gaps encourage this study and they are not rhetorical, but real limitations in analysis that inform specific design decisions.

The first is that there is no joint examination of FinTech and Digital Transformation. Most of the extant cross-country studies consider them two separate issues, with two separate literatures, two estimation frameworks and two sets of policy implications. In the literature on FinTech and sustainability, the studies usually use a single proxy, such as mobile phone subscription rates, internet penetration or a composite indicator of financial inclusion, whereas the literature on digital transformation uses indices of ICT infrastructure, broadband penetration or digital economy without considering the financial inclusion dimension addressed by FinTech.

The analytical problems arise from the fact that the two forces are not independent, but complementary: digital transformation creates the connectivity and device ownership that makes FinTech more accessible, and FinTech channels the income and productivity gains of digital transformation into demand for financial services.

The study of them individually yields exaggerated and incomplete estimates. This study is designed to fill this gap, estimating both within the same empirical framework, which allows direct comparisons of their relative magnitudes, their interaction effects, and their joint conditioning by EPU, which to the author's knowledge has no direct precedent in the cross-country sustainable development literature.

The second gap follows directly from the first: Most studies focus on one technology driver, most focus on one sustainability outcome and this is also analytically inadequate. Research on the impact of FinTech or digital transformation on sustainable development tends to be limited to a single indicator, such as income, a pollution indicator (e.g., CO_2 emissions), or a composite indicator (e.g., HDI, EPI); rarely both. This division is not sufficient since sustainable development, as defined, must be made on both human welfare and environmental quality. A technology that enhances human welfare at the expense of the environment has not yet become sustainable development, it is just a trade for another dimension. Estimating HDI and EPI together in a moderated framework is the only way to answer the question of integrated sustainability. The recent study by Sayari et al. (2025), which employs both outcomes and FinTech and digital economy proxies, but includes a geopolitical risk moderator instead of EPU and a sample of 30 countries from 1990 to 2023 that is not specifically geared towards the developing economy institutional context of primary interest here, is similar in spirit. This study is a dual-outcome study that fills the gap by applying it to developing and emerging economies between 2010 and 2022.

The third and most important gap is that almost no current study considers the question of whether these technology-sustainability relationships are actually observed in policy-uncertainty conditions, which are the conditions in most developing economies. Previous cross-country research generally makes an implicit assumption that the impact of technological investment on sustainable development is unconditional and that the average impact of technological investment on sustainable development is measured without questioning whether the impact varies systematically with the quality and stability of the institutional environment. While well documented in the wider economics literature Baker et al. (2016); Bloom (2009), EPU has been largely ignored as a moderating factor in the technology-sustainability nexus. This is consequential because the current evidence does not provide an answer to the most pressing policy question for developing and emerging economies: does digital investment work in environments of high and persistent policy uncertainty? The limited studies that do include institutional quality rely on static indicators such as rule of law indicators, governance scores, and regulatory quality rankings, none of which are specifically designed to measure the dynamic, time-varying policy instability that EPU aims to measure.

A country's rule of law score changes over time, and is only a partial indicator of the short-to-medium term evolution of policy predictability, which directly influences investment decisions. EPU, on the other hand, is a time-varying, high-frequency measure of exactly the institutional volatility that real options theory has suggested is the cause of the disincentive to investment in the face of uncertainty. This study aims to fill this gap by examining the moderation role of EPU in 45 developing and emerging countries from 2010 to 2022.

A fourth contribution goes beyond the conceptual gaps and seeks to answer the question of how EPU is measured and why the conventional method underestimates its impact. A common practice is to use the period average EPU, which assumes that a decade of moderate uncertainty is the same as a decade of high-low alternating uncertainty in terms of their impact on investment and development. But real options theory suggests that this is not true: the option value of postponing an investment is not a linear function of the average uncertainty but depends on the persistence and accumulation of the uncertainty over time. The time-weighted EPU formulation used in this study corrects for this by assigning weights to each EPU observation both by the magnitude and by the time of the observation in the history of policy change, which results in a measure that reflects the cumulative impact of chronic uncertainty, rather than the average. This is a methodological innovation in the EPU literature itself, and has implications that go beyond the specific technology-sustainability application discussed here.

These four gaps together create a space in the literature that this study fills, with the joint examination of FinTech innovation and digital transformation, estimated within a dual-outcome sustainable development framework and moderated by a time-weighted EPU measure, across a sample of developing and emerging economies selected specifically because it is in these institutional contexts where the technology-uncertainty-sustainability nexus is most consequential and least understood. Every gap can be directly linked to a specific design decision from Chapter 3, a specific hypothesis from this chapter, and a specific finding from Chapter 4.

1.4 Research Questions

This study is guided by five research questions that collectively address the conditional relationship between technological innovation and sustainable development:

1.4.1 Research Question 1

Does FinTech innovation contribute to sustainable development across countries, particularly in terms of human development (HDI) and environmental performance (EPI)?

1.4.2 Research Question 2

Does Digital Transformation contribute to sustainable development across countries, particularly in terms of human development (HDI) and environmental performance (EPI)?

1.4.3 Research Question 3

Does Economic Policy Uncertainty moderate the relationship between FinTech innovation and sustainable development?

1.4.4 Research Question 4

Does Economic Policy Uncertainty moderates the effect of digital transformation on sustainable development across countries?

1.4.5 Research Question 5

Do cross-country differences in technological readiness and economic policy stability influence the strength and direction of the relationships between FinTech innovation, digital transformation, and sustainable development?

When put together, these five questions will help to answer the main thesis of this study: that the relationship between technology and sustainable development is not unconditionally good, but is systematically structured and in high-uncertainty environments, substantially weakened by the stability and predictability of the institutional environment in which technology is used.

1.5 Research Objectives for This Study

The research objectives of this study are developed to directly and specifically answer each of the four research questions above. They are expressed in directional form, that is, not merely what is to be examined, but what the theoretical framework and the previous empirical evidence leads the study to expect, and thus makes the objectives falsifiable and the subsequent findings interpretable against a clear prior expectations:

1.5.1 Research Objective 1

To examine the effect of FinTech innovation on sustainable development.

1.5.2 Research Objective 2

To analyze the influence of digital transformation on sustainable development

1.5.3 Research Objective 3

To evaluate how Economic Policy Uncertainty moderates the relationship between FinTech innovation and sustainable development.

1.5.4 Research Objective 4

To evaluate how Economic Policy Uncertainty moderates the relationship between Digital Transformation and sustainable development.

1.5.5 Research Objective 5

To identify whether economic policy uncertainty alters the effectiveness of digital transformation and financial innovations in improving sustainability.

1.6 Problem Statement

Governments and international development institutions have placed a specific bet that growth of FinTech and digital transformation will lead to sustainable development without the need for parallel investments in the institutional conditions that surround the technology (United Nations Development Programme, 2022; World Bank, 2022). This is not a marginal assumption, as UNCTAD (2025) reports that financing for digital development is one of the largest and fastest-growing streams of investment flows to developing economies, but that the returns on this investment are still largely assumed, rather than empirically proven, especially in terms of the institutional context in which it is applied.

The problem in practice is that this assumption has been little tested against the actual condition that most developing economies face: sustained economic policy uncertainty (Baker et al., 2016). The general investment literature has well documented that policy uncertainty can reduce irreversible investment, through a real-options mechanism (Dixit and Pindyck, 1994; Bloom, 2009) and the deployment of digital infrastructure and FinTech platforms is exactly the type of investment that is most susceptible to this effect.

However, this mechanism has yet to be systematically applied to determine if it also applies to the sustainable development returns to technology investment specifically. In the current context of high uncertainty in macroeconomic and regulatory environments, the investment strategies in place may be over-optimistic about the potential of technology and underestimate the institutional changes needed to unlock it.

This separation has implications that go beyond the academic level of accuracy. The investment-deterring impact of policy uncertainty is also moderated by institutional quality, with the poorest institutional quality economies likely to suffer the greatest losses to returns on investment in digital development, where investment is most heavily targeted (Farooq et al., 2022; UNCTAD, 2025). In the case of sustainable development returns, if they are systematically lower or even non-existent when policy uncertainty is high, then closing the sustainable development gap in these economies is not just a technology-financing problem; it is an institutional-credibility problem that can't be solved with technology financing. It is therefore essential to first determine whether and to what extent Economic Policy Uncertainty conditions these returns, before the allocation of digital development financing can be done responsibly, rather than just left to the literature.

1.7 Significance of the Study

The results and contributions of this study are relevant to four groups of users: national policy makers in developing and emerging economies who design digital investment and macroeconomic stabilization policies; international development institutions and bilateral donors who allocate resources for technology financing; academic researchers who build on the cross-country sustainable development and institutional-uncertainty literature; and, more broadly, practitioners in the FinTech and digital infrastructure sectors who work in institutionally unstable environments.This study has three levels of analysis and each addresses one of the limitations of the literature available: methodological, empirical and policy. Together, these contributions advance the field, but in ways that alter the understanding, measurement, and response to the relation between technology and sustainability.

1.7.1 Methodological Significance

The methodological contribution of this study is the framework based on the diagnosis, which is very rarely used in the technology-sustainability literature and essential for drawing plausible causal inferences from cross-country panel data. Unlike the majority of the literature which uses simple fixed-effects or OLS estimation without any systematic testing of the properties of the data that warrant the use of one or the other estimation strategy, this study tests the data properties systematically and makes the methodological decisions based on the results of the sequence of tests. In particular, the study conducts the Pesaran (2004) cross sectional dependence test, the Augmented Dickey-Fuller panel unit root tests, the residual based cointegration tests, the Hausman specification tests, the variance inflation factor analysis, Breusch-Godfrey-Wooldridge serial correlation tests, Breusch-Pagan heteroskedasticity tests, slope heterogeneity tests, and Durbin-Wu-Hausman endogeneity tests. These diagnostics feed into the next design choice, which results in an empirically justified (not conventionally selected) estimation framework i-e System GMM for HDI dynamics, Dynamic OLS for EPI long-run cointegration, and FGLS with Driscoll-Kraay standard errors as a robustness check against spatial correlation (Pesaran, 2004; Driscoll and Kraay, 1998). Such methodological transparency leads to the strengthening of the credibility of the conclusions and offers a replicable template for future cross-country research in this literature.

1.7.2 Empirical Significance

This study has three specific contributions to knowledge.This study has three contributions to knowledge that are of an empirical nature.

First, it is one of the few cross-country empirical studies to measure both HDI and EPI as outcome variables in a single moderated framework; this is what the Brundtland framework calls for, but has not been achieved by previous empirical research. This study tests the impact of technology on human welfare and environmental performance at the same time, and finds out whether technological investments lead to real integrated sustainability or simply shift the developmental trade-offs (Sayari et al., 2025; Balsalobre-Lorente et al., 2025).

Second, it resets the time-weighted EPU operationalization as opposed to the contemporaneous EPU level used in almost all of the existing EPU-investment research, which reflects the simple level of policy instability. This innovation has implications beyond this study, as a measure of the cumulative effects of continued policy uncertainty can be applied anywhere where the cumulative effects of sustained policy uncertainty are theoretically relevant (Baker et al., 2016; Dixit and Pindyck, 1994).In addition, this study estimates the innovation and digital transformation of FinTech together in the same empirical framework, as opposed to the existing literature, which is largely composed of studies conducted in isolation, in their own disciplines.

Third, this study provides a directly comparable evidence on the relative magnitudes, interaction effects, and EPU-conditioned returns of both technological forces simultaneously, as opposed to the existing literature, which is made up of studies conducted in isolation, in their own disciplines.

The joint estimation design generates disaggregated evidence of the effects of a technology, which is something that neither composite-index designs nor single-technology studies can achieve, and directly tackles the policy need for integrated digital development strategies in developing and emerging economies (Wang et al., 2025; Balsalobre-Lorente et al., 2025).

1.7.3 Policy Significance

The moderation findings have the most direct policy implications, which offer actionable guidance to governments, international development institutions, and bilateral donors.

The fact that EPU systematically reduces the sustainable development returns to both the innovation of FinTech and digital transformation suggests that the effectiveness of digitalization agendas which have been at the core of sustainable development strategy in almost all international institutional programmes United Nations Development Programme (2022); World Bank (2022) relies heavily on macroeconomic and policy stability in which they are deployed.

The governments of developing and emerging economies, in particular, should not only strive to have good governance, but make regulatory credibility, fiscal predictability and institutional stability prerequisites for digital investment to realize its sustainable development potential.

In the case of international development institutions designing technology-based development programs, it means that policy stability assistance (such as the development of regulatory frameworks, improvement of public financial management and central bank capacity building) is needed if technological investment is to have a return on investment that is commensurate with its cost.

This study clearly shows that the institutional setting for the deployment of technology is as important as the technology itself, and for bilateral donors, that is a key consideration when deciding where to invest in digital transformation in high-EPU settings.

1.7.4 Policymaking Significance in Developing Economies

The policy implications for the developing and emerging economies are clear. The point is not that FinTech and digital transformation are not working, as this study shows that they are on average improving human development, and in the right models. The point is that the effectiveness of these technologies depends on the policy context: best in stable policy environments, and worst or even nonexistent in high and long duration policy uncertainty. Policy makers who invest in mobile payment infrastructure or digital transformation at the same time as they create policy uncertainty by making unpredictable fiscal moves, policy changes, or monetary policy uncertainty are playing into their own hands. The disruptive nature of the institutions they create undermines the uptake and effective use of the technologies they seek to encourage. The practical implication is not to pick one or the other, but to sequence and coordinate technology policy and institutional stability.The practical implication is not to choose either technology policy or institutional stability, but to sequence and coordinate them together (Baker et al., 2016; Bloom, 2009; United Nations Development Programme, 2022).

1.8 Organisation of the Document

This thesis is divided into five chapters. Chapter 1 , the current chapter, has presented the research context, theoretical framework, research gap, questions, objectives, problem statement, and significance of the study. Chapter 2 elaborates the entire literature review and theoretical framework, summarizing evidence on FinTech, digital transformation, and EPU in relation to HDI and EPI, and concludes with four directional hypotheses. Chapter 3 introduces the research method, including sample construction, operationalization of the variables, the complete pre-estimation diagnostic sequence, and the rationale of the multi-estimator framework that is used. Chapter 4 presents and discusses the empirical findings of all models and outcome variables, and combines the findings with the theoretical framework and existing literature. Chapter 5 ends with a conclusion of the main findings, policy implications, study limitations and future research directions

Chapter 2

Literature Review and Theoretical Framework

2.1 Overview: The Evolving Story of Technology and Sustainable Development

Development has not always occurred in a linear manner. Throughout most of the post-war period, the only way to gauge a nation's progress was in terms of its production, trade, and accumulation of. Production, trade, and accumulation were the only ways to gauge a nation's progress through most of the post-war period. By the end of the twentieth century, however, a significant change in intellectual and policy thinking occurred: the idea that growth was enough to bring about human well-being, and that growth was adequate to keep human life on the planet on which it depends, was rejected. This recognition led to a concept of sustainable development, which took the approach of not pushing one of the three pillars of welfare, environment and economy to the detriment of the other two, but rather treating them as equal partners and all contributing to a single, long-term goal (Brundtland Commission, 1987; United Nations Development Programme, 2022).

This conceptual change coincided with a revolution of another kind in the world. The digital technologies took over almost all aspects of human activity starting from late ninetieth and picking up pace in the early twenty-first centuries and twenty-tens, with a massive surge during the 2010s. The Internet connected remote communities with the rest of the world. Cell phones enabled access to financial and information services for people who had not previously been part of a formal banking system. As these technologies abounded, a new question began to surface in both the academic and policy arenas: can digital transformation and FinTech innovation not only increase economic efficiency, but also be real and substantive contributors to sustainable development?

This chapter develops the intellectual infrastructure necessary to answer this question. It starts with conceptual and measurement aspects of sustainable development: What is progress and why, and the fact that the Human Development Index (HDI) and the Environmenal Performance Index (EPI) are the most comprehensive available operationalization of the concept, and what the global trends in both indices tell us about the urgency of this research programme. It then moves to the two major independent variables at the heart of this study, which are digital transformation (measured by a composite index of internet access, mobile connectivity, ICT infrastructure and digital trade) and FinTech innovation (measured by the IMF Financial Access Survey digital payment transactions). The chapter maps out each instance and summarizes the literature-based evidence of their relationship with sustainable development, starting with where there is positive evidence, but being honest with null and negative evidence and then synthesizing what is known and what is questionable. The chapter then explores the institutional variable that shapes the picture as a whole: Economic Policy Uncertainty. A directional hypothesis is immediately derived from the evidence reviewed at the end of each substantive section.

The chapter draws from the literature on development economics, financial economics, environmental science and institutional theory. Over the last ten years, the digital transformation, FinTech, and multidimensional sustainability measures have coalesced into a new research program; it has been gaining momentum in recent years and patterns are starting to emerge that are becoming more coherent. The following is a frank description of the current state of that literature, what it has proved and what is still to be proved.

2.2 Sustainable Development: The Conceptual and Measurement Foundation

2.2.1 From GDP to Multidimensional Well-Being

In its intellectual aspect, sustainable development is a story of the dissatisfaction with the narrow set of indicators, by which progress has been measured so far. GDP was the main indicator of success during much of the post-war period. By the 1980s, however, a growing group of economists, philosophers, and policymakers had come to understand that there was a basic mismatch between the level of aggregate incomes and the actual conditions of health, education, freedom, and opportunity that would allow people to prosper (Sen, 1999). At the same time, and in a fundamental sense, there was a parallel concern that economic growth without environmental limits was self-defeating to mortgage the future in order to pay for the present that crystallised in the landmark Brundtland Commission report of 1987 (Brundtland Commission, 1987).

In response to these criticisms, the United Nations Development Programme (UNDP) created the Human Development Index (HDI) in 1990. The HDI, based on Amartya Sen's Capabilities Approach, provided a new and alternative definition of development that focused on what people could be and do, rather than what they could buy. It does so by using three normalised dimension indices: life expectancy at birth, mean years of schooling, and expected years of schooling, and gross national income per capita adjusted to purchasing power parity. Importantly, these dimensions are measured using the geometric mean, not simply summing the scores, so that surpluses in one dimension cannot make up for deficits in others e.g., a country that is rich, but poorly educated and unhealthy fails to achieve a high score on HDI, as its citizens' development is not taking place in any broad sense (Haq, 1990; Ranis et al., 2000).

The ecological aspect that HDI aims to exclude is covered by the Environmental Performance Index (EPI), which is a joint initiative of Yale University's Center for

Environmental Law and Policy and Columbia University. The EPI is a biennial report that analyzes data from 32 performance indicators grouped into 11 categories i-e ecosystem vitality, climate change mitigation, air quality, water quality, biodiversity, and environmental governance , each of which is scored out of 100 points. The strengths of the EPI are that it is rigorous, comprehensive, and that, unlike any single indicator, such as CO_2 emissions per capita or deforestation rates, it accounts for the complexity of a country's relations with nature, factors of environmental governance and ecological preservation that are systematically ignored by carbon-centric indicators Yale Center for Environmental Law and Policy (2022).

The rationale for using both HDI and EPI to define sustainable development in this study is that a country that develops human welfare at the expense of ecological systems, or maintains an ecological system at the cost of human deprivation has not achieved what the Brundtland framework requires. The dual-outcome design directly examines this integrated notion of sustainability, as opposed to taking for granted the convenient yet analytically problematic single outcome measure.

The usefulness of such a dual approach is supported by Sayari et al. (2025) who employ both of these indices in a cross-country panel in order to assess the developmental impact of digital transformation and FinTech, and record the trade-offs between human welfare and environmental performance that a single-index framework systematically hides. Likewise, Balsalobre-Lorente et al. (2025) demonstrate that the human development and environmental performance outcomes of ICT and digital technology are significantly different, meaning that estimating both simultaneously is desirable ,if not necessary.

2.2.2 Global Sustainability Trends and the Urgency of This Research

The results of this study must be considered in the context of the global trends of both these indices. The unprecedented progress over the past 30 years before COVID-19 was even in existence was solid but precarious. By 2019, the proportion of people in extreme poverty (living on less than USD 2.15 per day) had declined from around 36 per cent to less than 9 per cent, one of the biggest successes in economic history. Life expectancy at birth has increased from 65 years in 1990 to more than 73 years in 2019. Near-universal access to primary education was achieved in most areas. These gains were tangible, significant and widespread.

But as 2020 and 2021 have shown, these advances have been uneven, environmentally unsustainable, and fragile institutionally. The COVID-19 pandemic was the most widespread policy uncertainty shock of the study period, causing a massive backlash in regulations, emergency fiscal policies, and an unprecedented series of monetary policy actions whose uncertainty would be captured by the time-weighted EPU formulation, used in this study, specifically.

The United Nations Development Programme (2022) reported the first two-year drop in global HDI since the index was created in 1990 and lost around 5 years of development progress in just two years. The impact was not uniform; countries with less strong fiscal systems, fewer health care facilities, and where more people work in the informal sector experienced the worst and longest impacts, particularly the developing economies which make up the sample for this study.

At the same time, global CO_2 emissions which dipped slightly during the pandemic-related slowdown in 2020 hit a new record in 2021 of 36.5 billion tons, making it clear that none of the underlying causes of environmental harm have changed materially during the pandemic's economic disruptions. (Yale Center for Environmental Law and Policy, 2022)

These two headwinds are not just numbers they are a testament that the institutional environment is no longer a neutral backdrop for development, but a key factor in whether investments, technologies, and financial innovations will achieve their development potential. This is the main idea that leads to the moderating variable of Economic Policy Uncertainty in this study. The Global Findex 2025, the world's largest and most comprehensive financial inclusion database, presents for the first time the Digital Connectivity Tracker, documenting that, since 2021, adults in developing economies who saved in a financial account rose by 16 percentage points, to reach 40 percent in 2024, the strongest increase in more than a decade, pointing to continued acceleration in the financial inclusion momentum this study's sample captures, in the post-estimation period (World Bank, 2022). The trends set the agenda for understanding what can catalyse positive change in the SD outcomes and the potential of digital financial inclusion as a catalyst for that change, given stable institutional environments.

2.2.3 The Technology-Development Connection: Early Evidence

The relationship between technological development and the process of sustainable development is not a new discovery. Technology diffusion has been known to be one of the most important contributors to productivity growth, which leads to improvements in living standards over time (Romer, 1990).

What is relatively newer, however, is the recognition that particular types of technology, financial technology and digital infrastructure in particular can impact sustainable development not only through the direct path of productivity and income growth, but also more directly, through increased access to financial services, improved information flows between actors and sectors, more efficient use of natural resources, and the development of government and firm capacities in managing complex environmental issues.

Singh and Jyoti (2023) systematically review the impact of digitalization on sustainable development outcomes in countries and identify a consistent positive relationship between indicators of ICT development, human development, and environmental outcomes, with greater impacts found in lower-income economies where baseline levels of connectivity are low and the benefits of digital investments are therefore greater. Kaggwa et al. (2023) report that the digital transformation, which they define as adopting mobile technology, expanding internet infrastructure and expanding digital platforms, has helped diversify GDP in emerging economies, stimulate growth in the service sector, and enhance the delivery of public services. The link between development of ICTs and energy intensity and environmental outcomes is confirmed in a well-replicated study of the country level found by Salahuddin and Alam (2016).Early evidence that the technology-environment relationship is not only real but also well-established in the empirical literature comes from a widely replicated study at the country level by Salahuddin and Alam (2016).

2.2.4 Innovation as a Structural Driver of Development: Schumpeterian Foundations

The conceptual connection between innovation and development that has been discussed in this literature review can be traced back to Schumpeter (1934, 1942) seminal work on economic development as a process of innovation and not just of incremental accumulation of factors. Schumpeter's theory of creative destruction is a theory of development as a process of constant disruption, whereby new technologies, products, and organizational structures continually replace old ones, creating productivity gains that are not possible through incremental efficiency improvements within a fixed structure.

Schumpeter's theory of growth is different from classical growth theory because he did not assume that technological change is a background phenomenon, but instead he made innovation the driving force of structural economic change, and innovation is the work of entrepreneurial actors who are willing to take the risk of changing the economic status quo.

This Schumpeterian base is directly applicable to the digital transformation and FinTech innovation explored in this study. Mobile money platforms, digital payment systems and infrastructure-enabled service delivery are not simply additions to the existing financial and administrative systems, but exactly the sort of innovation Schumpeter described as the engine of economic growth. This lineage also predicts a theme that is central to this study: the returns of Schumpeterian innovation are especially sensitive to the stability of the environment in which entrepreneurial risk-taking takes place, a theme that is extended empirically in this study by the concept of Economic Policy Uncertainty (EPU) in Section 2.5. The endogenous growth model outlined in Section 1.2.1, which is based on Romer (1990), can be interpreted as a formalization of this Schumpeterian observation:

creative destruction becomes a tractable model of knowledge-driven increasing-returns growth.

This preliminary evidence is the basis for the general feasibility of a positive relationship between technology and sustainability. It has also brought to our attention some interesting cautionary points. The impacts can vary significantly by geographic area and income. The mechanisms by which technology affects sustainable development are often vague. But most importantly, the impact of the institutional context (in particular the regularity and stability of economic policy) on these relationships is rarely studied directly. These dimensions are explored in the following sections:

2.3 Digital Transformation and Sustainable Development

2.3.1 Digital Transformation as a Systemic Force

Digital transformation is the economy-wide deepening and intensification of digital connectivity, information processing power and technologically facilitated services. This includes Internet penetration rates, Internet access quality, mobile subscription coverage, ICT goods exports, volumes of digital trade and mobile broadband coverage. As these dimensions grow together, they are not only accelerating individual transactions but also changing the information environment in which all economic and social activity occurs, lowering the cost of information transfer, advanced information coordination, and improving the ability of governments, firms and households to make informed investments, use resources and deliver services (Kaggwa et al., 2023; Wang et al., 2025). This systemic nature is what makes digital transformation different from any particular application that is constructed on it: FinTech is one particular application layer built on top of digital infrastructure , digital transformation is the infrastructure itself and the impacts of its sustainable development are felt at the same time in all sectors of economic and social life.

This study operationalizes digital transformation by using a principal component analysis composite index (DigiTrans) based on five World Bank World Development Indicators (WDIs): mobile cellular subscriptions per 100 population, internet users as a percentage of population, broadband subscriptions per 100 population, high-technology exports as a percentage of manufactured exports, and ICT services exports as a percentage of GDP. The multi-dimensional composite is intentionally constructed to capture the wide range of a country's digital infrastructure status instead of a single dimension, as the sustainable development impacts of digital transformation are felt across all of these channels (Balsalobre-Lorente et al., 2025; Kaggwa et al., 2023).

2.3.2 Digital Transformation and Human Development: Continuous and Sustained Evidence

The empirical literature on digital transformation and human development is more consistent than the literature on technology-environment, with the mechanisms being more direct and the impacts more immediate. In the case of online education, the students in remote areas who do not have access to high-quality teaching resources can benefit from the improvement of internet connectivity. Mobile broadband connectivity enables telemedicine, remote diagnostics and health information services, which enhance health-seeking behavior and the efficiency of the healthcare system. Digital public services such as electronic identification, mobile government payments, online administrative registration, lower the administrative hurdles that disproportionately affect low income groups and improve effective access to social protection programmes. All these channels are directly connected with the education and health aspects of HDI.

As mentioned in Section 2.2.3, digitalization indicators are consistently positively related to HDI on multi-country panels, and the impact is stronger in lower-income economies where connectivity is lower. At the channel level, Kaggwa et al. (2023) report on the consistent findings that ICT adoption improves labor productivity, promotes service sector development and institutional modernization in emerging economies. The World Bank Global Findex 2025 shows that 79 percent of adults worldwide now have an account, and mobile money and digitally enabled accounts are changing financial behaviour and economic resilience, which is evident in the income and health aspects of HDI (World Bank, 2025). Wang et al. (2025) further explore the agricultural digital transformation, revealing that digitalization of agriculture, particularly through precision agriculture and digital supply chains, improves rural incomes and food security, and lowers resource waste, which are mechanisms that are applicable beyond the specific contexts investigated.

Balsalobre-Lorente et al. (2025) conclude that improving ICT infrastructure is one of the most robust drivers of SDG attainment in their multi-country sample, and is most effective for SDG 4 (education), SDG 3 (health), and SDG 10 (economic opportunity).

The uniformity of the digital transformation-HDI relationship that emerges from these studies suggests that there is a common mechanism to the relationship: in any economy, the cost of information decreases with increased connectivity, and the decrease in the cost of information creates efficiency gains in human capital investment. This is true in either of the two cases, whether the country is a low-income Sub-Saharan African economy with its first reliable mobile broadband connection, or an upper-middle-income Asian economy with next-generation ICT infrastructure. This effect is most pronounced at the lowest levels of digital access, but is present across the digital development spectrum.

2.3.3 Digital Transformation and Environmental Performance: A Dual Character

Digital transformation and environmental performance have a dual nature, as the same drivers that make digital infrastructure economically powerful can, depending on context and development stage, have a positive or negative impact on environmental performance, as described in the literature. There are several reinforcing pathways for the positive environmental channel. Smart grids minimize electricity transmission losses with ICT. Digital sensors and satellite data guide precision agriculture to optimize fertilizer and water use. Digitization of supply chains reduces logistical inefficiencies that generate unnecessary fuel consumption. From a macroeconomic perspective, the structural transition to digital service industries with significantly lower resource use is associated with a decrease in ecological footprints (Manu and Asongu, 2025; Salahuddin and Alam, 2016).

Digital transformation also enhances environmental governance by supporting better pollution monitoring, more transparent regulation enforcement, and better dissemination of environmental information to citizens, companies and policy makers. Li and Shu (2025) conclude that the use of digital technology improves green innovation efficiency by reconfiguring information sharing mechanisms that lower the cost of cleaner production. Nguyen et al. (2020) offers cross-country evidence that the ecological footprint in the G20 economies is negatively correlated with ICT trade, which is in line with the resource-efficiency mechanism.

The negative channel, however, is not a figment of imagination and must not be ignored. Digital infrastructure is a significant consumer of electricity, data centers, telecoms networks and device manufacturing all have a carbon footprint. These energy needs grow with the advancement of digital transformation, and in economies where electricity generation is mostly based on fossil fuels, this can intensify emissions and lower EPI scores. This scale effect is in line with the Environmental Kuznets Curve (EKC) theory, which suggests that the environmental impact of digital transformation can be negative at the initial stages of digitalization, but becomes positive as the economy becomes more efficient (Grossman and Krueger, 1995; Hou et al., 2024). The direction of the digital transformation-EPI relationship is thus dependent on a country's development status, the cleanliness of its energy grid and the capacity of its institutional environment to harness the efficiency potential of digitalization while managing the costs of its energy demand.

The digital divide, the systematic disparity in access to and ability with digital technologies across and within countries, is a further qualification to the positive story of digital transformation as a universal development driver. According to UNCTAD (2025), greenfield investment in digital services in developing countries increased from USD 6 billion in 2020 to USD 37 billion in 2024, but almost 80 percent of this investment was made in just 10 countries, leaving the remaining developing economies with a digital infrastructure investment shortfall of USD 1.6 trillion. This concentration is, in turn, shaped by the institutional context: digital investment flows are more likely to go to countries with stable and predictable policy frameworks. Ndoya and Asongu (2024) report that there are significant regional differences in digital access, and that from low starting points in Sub-Saharan Africa and South Asia, context-specific solutions are required because the problems of digital transformation in these regions are fundamentally different. This heterogeneity is the very reason that motivated the cross-country panel design of this study, and the use of System GMM estimation that explicitly models country-level unobserved heterogeneity.

In a heterogeneous panel study of developing countries, Akram et al. (2020) conclude that the net effect of digital infrastructure improvements on carbon emissions is negative after controlling for the proper country-level heterogeneity, which is consistent with the general conclusion that efficiency channels dominate scale effects in properly specified models.

This is supported by Manu and Asongu (2025), who found that the adoption of ICTs in their sample of countries has a positive impact on ecological pressure and also on human development outcomes, providing direct evidence of the dual positive impact of digital transformation for both sustainability dimensions.

2.3.4 Hypothesis Development: Digital Transformation and Sustainable Development

The evidence reviewed above is not balanced on both dimensions of sustainable development. The human development channel is relatively straightforward and uniform: investments in digital infrastructure lead to productivity, service delivery and welfare benefits that are well replicable in different country contexts. The environmental channel is more complicated: digital transformation has a proven dual nature, with smart infrastructure and monitoring leading to efficiency and governance benefits, but also to higher energy consumption and, consistent with the Environmental Kuznets Curve, potentially to poorer environmental outcomes at earlier stages of digital and income development.

This asymmetry does not invalidate the argument for a directionality hypothesis; it is a theoretical expectation based on the Technology-Development Nexus and the Environmental Kuznets Curve that the relationship between digital transformation and sustainable development does not have to be the same in both human and environmental aspects. This study examines the two outcomes of HDI and EPI separately, and independently, from one another, and tests this expectation against each outcome separately, in the 45-country developing-economy sample and dual HDI–EPI structure this study employs:

H1: Digital Transformation positively and significantly impacts Sustainable Development.

2.4 FinTech Innovation and Sustainable Development

2.4.1 What FinTech Is and Why It Matters to Sustainable Development

Financial technology is not a single technology, but a family of technologies that offer financial services in a more efficient, accessible and inclusive manner than conventional banking systems. The relevance of FinTech to sustainable development is based on a well-documented structural failure of the traditional financial systems, namely that they systematically exclude large parts of the populations of developing economies from the formal financial services that are crucial for economic resilience, productive investment and improvement of human welfare (Demirguc-Kunt et al., 2018). Financial exclusion is an immediate obstacle to sustainable development: households without formal savings cannot invest in education or healthcare in the event of income shocks; small firms without access to capital are constrained in growth, employment and adoption of technology that increases productivity and welfare; communities with no payment infrastructure have high transaction costs that reduce income from productive and welfare-enhancing activities.

The empirical literature on the link between FinTech and SDGs is growing more and more. The cross-country evidence in recent years has corroborated the positive effects of fintech diffusion and digital financial inclusion on financial access and the speed of technology adoption by enhancing information transparency and transaction costs, which directly contributes to multiple SDG dimensions such as poverty reduction, inequality reduction, economic growth and infrastructure development (Banna et al., 2022; Choudhary and Thenmozhi, 2024; Daud and Ahmad, 2023). Most importantly, this literature indicates that it is a two-way street; that is, the relationship is mutually reinforcing, and when the institutional environment is sufficiently stable to support it, the inclusion and development of FinTech and SDG can be a virtuous circle.

In this study, the proxy for FinTech innovation is the value of mobile payment transactions as a share of GDP, which is provided by the Financial Access Survey by the IMF and is well defined, following established practice in the cross-country FinTech literature (Cevik, 2024). This measure captures the extent of digital payment adoption in the economies and not just the number of digital payment accounts, but the scale of digital financial activity relative to the size of the economy and directly operationalizes the financial inclusion pathway through which FinTech is anticipated to play a role in sustainable development. The selection of a single, well-founded proxy is motivated by the theoretical clarity of the financial inclusion mechanism, and by data availability limitations of the 45-country developing economy panel. This channel is still alive and kicking, as mobile money and digitally-enabled accounts are fueling financial behaviour and economic resilience in the very economies included in this study's sample, as evidenced by the largest increase in formal savings rates in more than a decade in 2024 (World Bank, 2025).

The mechanism of financial inclusion is the theoretical and empirical basis of the positive contribution of FinTech to human development. In developing economies, mobile money platforms have shown that digital payment systems can be quickly expanded to previously unbanked populations, providing households with new opportunities to save, remit and cope with income volatility that cash-only economies cannot accommodate (Demirguc-Kunt et al., 2018). Empirical evidence is consistently found to be associated with such gains with measurable improvements in the household consumption, health expenditure and educational investment—all direct inputs to the health and education dimension of HDI.

The M-PESA platform, which was introduced in Kenya in 2007, is the best known empirical example of this mechanism. It had already handled transactions that exceeded 40 percent of Kenya's GDP per year by the time it had been introduced 10 years ago, had brought in tens of millions of new users who had previously been unbanked, and had had measurable impacts on household consumption, poverty reduction and women's economic empowerment (Jack and Suri, 2014; Suri and Jack, 2016).

In 2021, mobile money transactions hit the one-trillion-dollar mark, with 866 million registered accounts in 90 countries, the largest documented formal financial access growth in economic history (GSMA, 2022). Since then, similar platforms have been rolled out in other parts of Sub-Saharan Africa, South and Southeast Asia, and Latin America, and adoption rates have closely mirrored the financial inclusion mechanisms the framework of this study aims to examine.

Danladi et al. (2023) carried out a systematic review and identified that financial inclusion through digital platforms has a positive impact on the following SDGs, namely SDG 1 (No Poverty), SDG 3 (Good Health and Well-Being) and SDG 4 (Quality Education) which are the three goals that are most directly reflected in the component dimensions of HDI. Saha and Qin (2023) conclude that the financial inclusion channel reduces poverty and enhances welfare in the developing world in a cross-country panel. Results from the cross-country panel corroborate the financial inclusion mechanism identified in previous studies, and directly replicated in this study, showing that FinTech innovation has a positive and statistically significant effect on HDI. The financial inclusion channel is a multi-faceted economic channel. Mobile money lowers the cost and risk of holding and moving value at the household level, which can allow households to save buffers that help them cope with shocks to income,a direct driver of the income and health components of HDI (Jack and Suri, 2014). World Bank (2025) found that 80 percent of adults that saved in emerging markets and developing economies said they were more resilient to emergencies, which was directly linked to their access to formal savings. The digital payment infrastructure also lowers transaction costs for small businesses using costly informal payment systems, freeing up resources for productive investments and allowing access to wider markets (Daud and Ahmad, 2023). Government level, digital payment systems can help deliver social transfers, subsidies and public wages more efficiently and effectively, and with less corruption, as evidenced by the impact on the reach and effectiveness of social protection programs in developing economies(World Bank, 2022). All of these channels are unique and complementary pathways between FinTech adoption and the outcome of income, health and education benefits measured by HDI. More critically, recent evidence shows that these pathways are two-way and reinforcing when the institutional environment is conducive. Adoption of FinTech and progress towards the SDGs are mutually reinforcing, with virtuous cycles of inclusion and development triggered and maintained when policy uncertainty is low enough for households and firms to trust and invest in FinTech. Adoption of FinTech and progress towards the SDGs are mutually reinforcing, with virtuous cycles of inclusion and development triggered and maintained when policy uncertainty is low enough for households and firms to trust and invest in FinTech (Banna et al., 2022; Choudhary and Thenmozhi, 2024). This bi-directionality is one of the theoretical arguments for the moderation analysis conducted in this study: the EPU mechanism not only dampens the direct returns on FinTech investment, but also breaks the virtuous cycle between FinTech adoption and sustainable development, which mutually reinforce over time.

2.4.2 FinTech and Environmental Performance Landscape: A More Complex Picture

The relationship between the FinTech and environmental performance is more nuanced than the HDI story and less consistent. There are multiple mechanisms that support the positive environmental argument for digital financial systems. Digital financial transactions do away with the need for physical branch networks, paper-based documentation, and cash logistics operations, all of which have non-trivial carbon footprints.

More importantly, FinTech can direct capital to green investments via sustainable finance platforms, green bonds, ESG-integrated loan products and climate fintech applications. This is just one example of the growing convergence of FinTech and environmental sustainability, as evidenced by the USD 2.3 billion raised by climate fintech startups in 2023 alone, according to the International Monetary Fund (2024).

Based on firm-level data, Wang et al. (2024) conclude that FinTech adoption lowers the carbon emissions of companies by three channels: enhancing resource allocation efficiency, decreasing the information barriers to green investment, and improving the transparency of environmental performance reporting.

In a systematic review that brings together 120 studies on the relationship between FinTech and green finance, Khan and Shahid (2025) conclude that when digital platforms expand access to sustainable finance, there is a strong positive synergy between the two, with FinTech driving financial inclusion and reducing transaction costs, and green finance directing capital towards low-carbon technologies, renewable energy and climate-resilient infrastructure. As of 2024, global investment in fintech products and services dedicated to climate change has exceeded USD 50 billion, and more than 60 percent of fintech startups have integrated ESG considerations into their business models, according to United Nations Development Programme (2025). However, the cross-country evidence is mixed, and a fair assessment of the literature has to face the null and negative results head on. The FinTech-EPI relationship often becomes weak or statistically insignificant when studies are conducted in multi-country settings and extensively account for income effects and country-specific heterogeneity. The rise in income that FinTech brings can, at least in the early stages of development, boost aggregate demand for goods, services and energy whose production imposes environmental costs—the conflict of interest that is the Environmental Kuznets Curve ((Grossman and Krueger, 1995; ?). The EPI is also a composite of 32 indicators that are much more extensive than the ones that are likely to be influenced by financial innovation in the short to medium term, such as biodiversity protection, marine health, heavy metal exposure, etc., and many of which are also influenced by long-term institutional and geographical factors that are more difficult to change quickly through financial innovation. The evidence that has been gathered so far indicates that the environmental effects of FinTech are real but less pronounced, more diverse and more context-specific than the impacts on human development, which this study confirms in fact. The green finance channel is another possible avenue by which FinTech could help to enhance environmental performance. Digital platforms can reduce the cost of accessing sustainable investment products and improve transparency around green financial flows, thereby allowing small investors, smallholder farmers, and micro-enterprises, who are most reliant on FinTech for financial access, to channel funds into sustainable land use, energy efficiency, and renewable energy adoption. But for this pathway to be realised, not only does the FinTech infrastructure need to be in place, but stable regulatory commitments to green finance frameworks are needed, commitments that are undermined by economic policy uncertainty."Recent firm-level evidence corroborates this green finance channel while confirming its sensitivity to policy uncertainty: Perera et al. (2026) find that green finance significantly improves corporate environmental performance, but this effect is systematically weaker under high economic policy uncertainty, consistent with the real options mechanism through which EPU discounts long-horizon environmental investment regardless of the financial channel through which it is deployed. This implies that, in theory, EPU reduces the environmental impact of FinTech's green finance channel, even before the channel can generate measurable EPI improvements over the medium run in the observation window.

2.4.3 Hypothesis Development: FinTech and Sustainable Development

The evidence presented above is also skewed in terms of the two aspects of sustainable development. The human development channel is well established: digital payment adoption is through the financial inclusion channel and the empirical evidence is direct and consistent across country contexts. The environmental channel, on the other hand, is not homogeneous: firm-level and platform-specific studies tend to report positive effects via green finance and resource-efficiency channels, while cross-country panel studies with income and heterogeneity controls tend to report null effects, with income-driven consumption growth offsetting the effects that would otherwise lead to environmental gains.

This is not a problem for the case for a directional hypothesis, but rather a theoretical distinction between a more established micro-level financial inclusion channel and a more contentious, context-dependent environmental channel. This study tests this expectation against each outcome separately, as they are not a combined sustainability index, but rather two distinct outcomes of HDI and EPI, in the sample of 45 countries used in this study that are developing economies.

H2: Fintech Innovation positively and significantly impacts Sustainable Development.

2.5 Economic Policy Uncertainty: The Institutional Moderator

2.5.1 EPU As Moderator

Economic Policy Uncertainty enters this study not as a control variable to be held constant, but as a moderator, a variable hypothesized to alter the strength or direction of the relationship between an independent variable and an outcome, rather than to independently drive the outcome itself. This distinction matters methodologically as much as theoretically: a control variable's coefficient describes its own direct association with the outcome, whereas a moderator's explanatory power is captured specifically through its interaction with the primary regressors i-e DigiTrans $\times$ EPU and Digital Payments $\times$ EPU in this study's specification. Treating EPU as a moderator therefore reflects a specific theoretical claim, developed below, that policy uncertainty does not independently determine sustainable development outcomes so much as it conditions whether digital transformation and FinTech innovation are able to deliver the returns theory predicts for them.

EPU is not modeled as a mediator in this study because it does not lie on the causal pathway between digital transformation, FinTech innovation, and sustainable development, technology does not generate policy uncertainty, nor does policy uncertainty generate technology adoption, as a mediating variable would require. Nor is EPU modeled as a simple control variable, despite its established direct associations with investment and development outcomes in the broader literature Baker et al. (2016); Bloom (2009), because a control variable's role is to hold constant a confound, not to condition the strength of another relationship. The theoretical case for EPU as a moderator rests specifically on real options theory (Dixit and Pindyck, 1994): policy uncertainty is hypothesized to alter the option value of committing to irreversible, capital-intensive digital investment, meaning its effect operates through changing how strongly digital transformation and FinTech innovation translate into sustainable development outcomes — not through independently producing those outcomes itself. This is precisely the functional definition of moderation: EPU is expected to condition the return on technology investment, not to substitute for it (Baron and Kenny, 1986).

Operationalizing EPU as a moderator carries direct methodological consequences, distinguishing this treatment from the way institutional-quality variables are typically handled in the literature, where they are frequently included only as linear controls (Section 1.3 discusses this as a specific gap this study addresses). This study instead specifies EPU's moderating role through explicit interaction terms , DigiTrans × EPU and Digital Payments × EPU estimated alongside the main effects of each regressor in Equations 3.1 and 3.2b. Under this specification, the main effect coefficient on a technology variable captures its association with the outcome when EPU is at its sample mean, while the interaction coefficient captures how that association changes as EPU rises or falls. A statistically significant, negative interaction coefficient, the pattern hypothesized in H3 and H4 , would indicate that EPU systematically dampens the technology-sustainability relationship, providing a direct empirical test of the real options mechanism described above, distinct from testing whether EPU itself independently predicts sustainable development outcomes.

This framing also clarifies a scope condition worth stating explicitly: because moderation is tested through an interaction term, its statistical detectability depends on the existence of a main-effect relationship for the interaction to condition. Where a technology variable shows no significant direct relationship with an outcome, a corresponding moderation effect may be theoretically valid but empirically difficult to isolate, since there is limited variation in the underlying relationship for EPU to be shown to alter.

2.5.2 Measuring Uncertainty and Why It Matters

Economic Policy Uncertainty is a metric of how uncertain the trajectory of government economic policy is to firms, households, and investors. In addition to the uncertainty that is always present in any forward-looking decision, economic actors are confronted with the extra uncertainty that comes with the policy decision whether it is tax rates, regulatory requirements, trade policies, monetary policy stance, or government expenditure priorities that makes long-term planning and irreversible investment much riskier. The most popular empirical indicator of EPU is the index of EPU developed by Baker et al. (2016), which is based on the frequency of newspaper mentions of words related to EPU, as well as tax code expiration uncertainty and forecaster disagreement on government spending and inflation. Baker et al. (2016) provide empirical evidence that the rise in EPU is followed by substantial and lasting reductions in investment, employment, and output growth, particularly in industries with a long horizon and high capital intensity, and that these effects last for several quarters.

The OECD Economic Outlook 2025 offers the latest macroeconomic confirmation of this mechanism: a one standard deviation rise in EPU is associated with a corresponding drop in business investment growth of around one percentage point in one year, peaking after four quarters, consistent with the empirical robustness of the EPU-investment relationship found in the foundational study by Baker et al.

(2016) in the current policy environment of high uncertainty (OECD, 2025). The OECD has identified the environment of high trade policy uncertainty in 2024-2025 as one of the direct drivers of the slowdown in productive capital flows that is hampering progress toward the Sustainable Development Goals around the world.

This study uses a time-weighted version of the EPU index, $EPU_{tw} = EPU(i, t) \times t(i)$, where $t(i)$ represents the time weight associated with observation i. is a country-specific time counter that is summed over the time period of observation. This time-weighting is an important conceptually insight that uncertainty that remains over time is more harmful than a temporary increase of the same magnitude. The ongoing uncertainty gradually erodes investor confidence, reduces strategic planning periods and fundamentally changes the risk calculation of investments with long-term time horizons in digital infrastructure and green technologies. The idea of accumulated uncertainty damage is based on the real options literature: If the value of waiting is high at all times, firms and policy makers can indefinitely delay commitments that would otherwise move sustainable development forward (Dixit and Pindyck, 1994; Bloom, 2009).

2.5.3 EPU and Investment Suppression Mechanism

The most basic way in which EPU impacts sustainable development is by curbing investment. Pastor and Veronesi (2013) demonstrate that political uncertainty is reflected in financial assets as a risk premium which raises the cost of capital and deters investment in projects that rely on stable policy conditions. Bloom (2009) shows that uncertainty shocks lead firms to suspend hiring and capital spending until uncertainty is resolved, particularly for irreversible technological investment. In a ten-year sample of publicly listed companies in the six Asian economies, Farooq et al. (2022) find that EPU has a significant negative effect on corporate investment decisions which persists and strengthens even after controlling for endogeneity (System GMM), and importantly, that the quality of the institutional environment moderates this relationship, with better institutions reducing the investment-suppression effect of EPU.

Digital infrastructure projects meet all three of the real options theory conditions that increase the value of the option to wait: irreversibility, capital intensity, and policy contingency. The returns on these investments are at the core dependent on the regulatory landscape of digital financial services, data protection and telecommunications licensing. As EPU increases, uncertainty about all of these policy dimensions increases at the same time, and the theoretically predicted reaction i-e a decrease in digital investment, a decrease in FinTech adoption, a decrease in sustainable development outcomes is what this study's moderation framework tests (Dixit and Pindyck, 1994; Bloom, 2009) .

EPU also has negative impacts on financial system efficiency that exacerbate its direct negative impact on investment. In a study that focuses specifically on the impact of EPU on the functioning of the financial system, (Aman et al., 2024) conclude that EPU has a negative effect on financial institutions and markets, with potentially serious consequences for the functioning of the financial system in general and for the economies of the world in particular, explicitly stating that future research should focus on the implications for FinTech-based financial systems. This study directly tackles the identified gap, offering the first systematic cross-country evidence of the moderating effect of EPU on the sustainable development returns to FinTech adoption.

2.5.4 Evidence of EPU and FinTech Adoption: Specific Evidence

Recent evidence suggests this uncertainty-reducing mechanism applies not only to aggregate investment, but also to the economic impacts of FinTech. Although FinTech has a positive moderating effect on corporate risk-taking and growth-oriented investment, it is significantly dampened by high economic policy uncertainty, as EPU negatively moderates the FinTech-risk-taking relationship(Liang et al., 2025) . This uncertainty-induced suppression is likely to be even stronger in developing economies: lower institutional buffers will lead to more cautious financial behavior as a result of policy uncertainty, which may offset the confidence boost that

FinTech adoption would otherwise bring. In developing economies, high EPU negatively affects the financial inclusion benefits of FinTech adoption by causing financial instability that compels households to return to cash and informal finance, which is the opposite of what mobile payment adoption during stable periods does, according to Danladi et al. (2023).

This reversal mechanism is especially harmful because it takes place in the economies with the greatest potential for digital financial inclusion and in the economies where the behavioral change from formal finance will have the greatest impact on household welfare.

The interaction between EPU and FinTech is also complicated by the diversity of the impact of EPU on the developing economy spectrum. Weaker institutional buffers in developing economies mean that policy uncertainty is more likely to become investment deterrence than in advanced economies, where policy uncertainty is less likely to become investment deterrence because of the strong institutional foundations in these economies (independent central banks, rule of law, credible regulatory agencies). EPU shocks in these settings have more direct and longer-lasting impacts on investment, are more likely to be associated with currency volatility and capital flight, and amplify the direct investment-deterrence effect. Adil et al. (2025) confirm that EPU has an impact on investor confidence and the cost of capital, which makes it an important factor in the responsiveness of the financial system and, as the authors point out, the EPU-FinTech nexus is different, and more harmful, in the institutional environment of developing economies than the evidence base from developed economies alone would suggest.

2.5.5 EPU and Digital Transformation: The Infrastructure Investment Channel

The moderating effect of EPU on digital transformation is similar but on a larger scale and with potentially more lasting impacts. Digital transformation requires investments in the long-term, over several years, in infrastructure such as broadband networks, spectrum allocation, telecommunications regulation, digital public administration systems, etc., which are not reversible in the short term or incrementally. Policy uncertainty is therefore a particular concern when it comes to investments that can meaningfully derail the digital transformation path of entire economies, as policy changes, regulatory frameworks shift in unpredictable ways and macroeconomic turbulence can affect fiscal capacity (Manu and Asongu, 2025).

In institutionally unstable policy environments, the returns to digital investment are not guaranteed, but systematically conditioned by the policy environment in which the investment takes place (Balsalobre-Lorente et al., 2025).

One of the key pathways is the relationship between EPU and environmental digital investment. Environmental sustainability is not just about investing in cleaner technologies, it is also about long-term regulatory commitments such as carbon pricing schedules, renewable energy mandates, pollution standards, and so on, whose effectiveness relies on their credibility over time.

If EPU is raised, these pledges are less likely to be taken seriously, because companies and investors have grounds for uncertainty about their ability to endure political changes or a financial crisis. This environmental policy uncertainty specifically lowers investment in renewable energy, green infrastructure, and clean technology adoption some of the most important ways in which digital transformation can boost EPI scores (Li and Shu, 2025; Manu and Asongu, 2025).

This mechanism finds direct precedent in Udeagha and Muchapondwa (2022), who demonstrate that EPU itself moderates the environmental Kuznets curve in South Africa, accelerating environmental degradation independent of the income-driven scale and technique effects the EKC framework typically emphasizes a finding this study's own EPU-dominance result on EPI is consistent with.

Han et al. (2025) extend this evidence to green innovation specifically, finding that EPU has a considerable adverse effect on green innovation across BRICS economies, though financial sector development partially bridges this gap reinforcing that the suppression channel identified in this study's DigiTrans $\times$ EPU interaction operates through a broader, well-documented uncertainty-innovation mechanism.

In the Chinese context, Chen et al. (2023) show that policy uncertainty hinders the innovation of green technology even if the technology is already available, suggesting that the environmental dividend of digital transformation depends on the credibility of the institutions.

The findings of Xu et al. (2025) suggest that digital transformation can buffer the negative impact of EPU on innovation through the reduction of information asymmetry and the enhancement of information processing, which is good news, but also means that the stabilizing benefits of digital transformation on the institution are dependent on having a sufficient level of baseline digital capacity to trigger them.

2.5.6 Hypothesis Development: EPU as Moderator

Given that real options theory suggests that uncertainty works through the investment channel that underlies both digital transformation and FinTech adoption, the impact of uncertainty should be felt as a moderating effect on the strength of the impact of the technology on sustainable development, not as an independent additive effect.

This is different from the moderation hypotheses H1 and H2, which would have predicted a direct link between EPU and sustainable development, but would have predicted that this link would be systematically moderated by EPU.

To test this, one must have hypotheses different from H1 and H2, and test them separately for each outcome:

H3: Economic Policy Uncertainty has a negative moderating effect on the relationship between Digital Transformation and Sustainable Development

H4: Economic Policy Uncertainty has a negative moderating effect on the relationship between FinTech innovation and Sustainable Development

2.6 Theorteical framework

This conceptual framework places Digital Transformation and FinTech Innovation (as operationalized in the form of digital payment adoption) as the main independent variables that directly affect two different, yet mutually necessary, sustainable development outcomes: the Human Development Index (HDI) which measures human welfare in terms of health, education, and income, and the Environmental Performance Index (EPI) which measures ecological quality in terms of 32 environmental indicators.

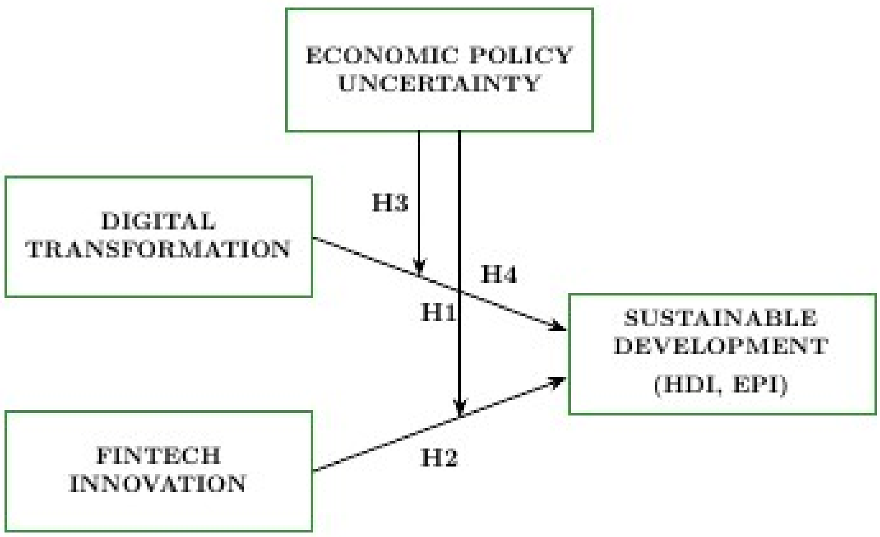

Figure 2.1: Conceptual Framework of the Study

The direct technology-sustainability pathways are not considered as absolute. To systematically moderate the returns to technological investment, across both pathways, Economic Policy Uncertainty is introduced as a moderating variable. To isolate the direct effects of technology and the conditioning effects of institutional uncertainty, two control variables are kept constant across the entire sample: GDP per capita and the Geopolitical Risk Index (GPRI).

The framework has three analytical layers that together reflect the enabling effect of technology on sustainable development, the conditioning effect of institutional stability on the extent to which this enabling potential is realised, and the outcome asymmetry between the effect of technology on human development (which is realised quickly through financial access and digital service delivery channels) and the effect of technology on environmental performance (which is realised slowly through structural lags, with EPU being the primary mechanism during the medium run observation window).

The framework is based on six related theories, which are elaborated in greater detail in the theoretical background section of Chapter 1: the Diffusion of Innovation Theory, Sustainable Development Theory, the Capabilities Approach, the Technology-Development Nexus, the Environmental Kuznets Curve, and the Uncertainty-Investment Framework. They form the intellectual underpinning of the estimation strategy, the structure of the hypotheses and the interpretation of the results in Chapter 3 and 4.

Chapter 3

Research Methodology

3.1 Research Design and Sample Construction

3.1.1 Overview And Rationale

In this chapter, the methodological framework is introduced on which the empirical investigation of the nexus between digital transformation, FinTech innovation and sustainable development is based. The analysis uses panel data methods to look at these relationships across a cross section of 45 developing and emerging economies between 2010 and 2022, focusing on the moderating effect of Economic Policy Uncertainty (EPU).

The research philosophy of this study is post-positivist, which assumes that the results of sustainable development and the relationship between sustainable development and technology and institutional uncertainty are real, but can only be known through empirical observation that is imperfect and probabilistic (Popper, 1959). This position is not a strict positivist one, which assumes direct, certain access to objective truth, but rather a post-positivist one that recognizes that all measurement, including the composite indices, standardized proxies, and imputed values used in this study, is subject to error, and that knowledge claims must be made probabilistically and open to falsification (Creswell and Creswell, 2018). This is evident in the methodological structure of the study, which is based on hypotheses that are formulated as falsifiable, directional statements (H1, H2, H3 and H4) that are tested against explicit statistical significance thresholds rather than treated as certainties, and in the systematic diagnostic testing of the hypotheses, the multi-estimator triangulation, and the explicit recognition of endogeneity and measurement limitations throughout Chapters 3 and 4, which reflects the post-positivist commitment to approximating rather than asserting objective truth through rigorous, falsifiable empirical inquiry.

The analytical design of this study is based on the conceptual distinction that is at the heart of its contribution: digital transformation and digital payment adoption are not synonymous proxies for the same phenomenon but two analytically different and complementary aspects of the technology-development nexus. The supply-side, enabling-environment dimension is digital transformation (operationalized in a composite infrastructure index, DigiTrans), which refers to the existence of mobile, internet, broadband and ICT infrastructure needed to allow digital economic activity to occur at scale. The demand-side, transaction-based dimension is digital payment adoption, operationalized as the IMF Financial Access Survey: whether the population is using the digital infrastructure for financial transactions or not, measured as the economic depth of mobile payment penetration relative to GDP.

A nation can be digitally transformed with low financial innovation (as in the case of infrastructure deployment with low formal financial use) or high financial innovation with moderate infrastructure (as in the Kenyan mobile money example). The study's ability to break the infrastructure channel from the financial adoption channel and directly compare the contributions of these two channels to sustainable development ,their sensitivity to economic policy uncertainty , is enabled by the study's focus on these two dimensions together, within the same estimation framework and across the same country panel.

The methodology section provides details on the data sources and the process of constructing the sample, including the reasons for excluding countries (Section 3.2); definitions and operationalization of variables and supporting literature (Section 3.2); the structure of the panel and how missing data were addressed (Section

3.3); diagnostic testing procedures and results (Section 3.4); and the rationale for choosing the estimators (Section 3.5). The guiding principle is transparency: all methodological decisions are documented with their empirical justification, to allow for independent evaluation and replication of analytical choices.

3.1.2 Data Sourcing And Sample Construction

3.1.2.1 Starting Sample Frame

The study uses an unbalanced panel dataset of 2010-2022, which is built using several international data sources. The original conceptual sample frame was designed to include all countries that the World Bank categorizes as low-income, lower-middle-income, and upper-middle-income countries, to provide the widest possible geographic coverage in a developing and emerging economy context that is the motivating context for this research. The starting frame was then adjusted based on the availability of data for the two FinTech channels: the digital payment variable is only available for countries with a well-developed mobile banking environment that report systematically to the IMF, which set the binding constraint on the composition of the sample. Countries with less than three observations on the primary regressor (digital payment transactions) over the 13-year period were excluded as this would leave more than three-quarters of the observations on the key regressor unobserved, which is not defensible (Little and Rubin, 2002; Sterne et al., 2009). The result of this process was a final sample of 45 countries.

3.1.2.2 The 45-Country Sample and Time Window

The 2010-2022 time window was chosen to meet two criteria. The first is the temporal scope, which needs to be long enough to reflect the digital transformation paths during the recovery from the financial crisis that started in 2008, a time when mobile banking infrastructure has been significantly scaled up in developing economies and FinTech platforms have started to operate at scale. Second, data availability: IMF FAS improved systematic data collection of digital payment data from 2011, and EPI biannual data became more comprehensive from 2010.

The 2022 cutoff represents the latest available data at the time of analysis, and allows for enough lead time for lagged effects to occur. An extension to 2023-2024 would include structural breaks during the post-pandemic policy normalization period and make it difficult to estimate long-run relationships.

Data preparation was done in a preliminary stage and 49 countries were identified as having digital payment data. Four were then dropped prior to imputation of other variables. Vietnam did not have any observations on the digital payment indicator over 13 years, making it impossible to identify within-country changes.

Tunisia had only one observation (2022) over 13 years, which is not enough for a reliable estimation. There were just two observations in Colombia (2021 and 2022) and in Honduras (2021 and 2022).

The systematic exclusion rule was applied such that countries with less than three observed values of the primary regressor on the FinTech regressor were excluded, as more than three-quarters of the country-level observations would have to be imputed for inclusion. This resulted in the final 45 countries sample.

3.2 Operationalization and Definitions of Variables

3.2.1 Dependent Variables

3.2.1.1 Human Development Index

The main dependent variable that captures the socioeconomic sustainable development is called Human Development Index (HDI). It is calculated as a geometric mean of three dimension indices that are normalized: life expectancy at birth (health), mean and expected years of schooling (education), and gross national income per capita (income) adjusted to purchasing power parity. The data comes from the UNDP Human Development Report, which is published every year, and has a range of 0-1.

The geometric mean specification is based on the UN sustainable development framework which states that a country cannot have a good score in one dimension without having a good score in the other, meaning that a country with a high score in HDI but a low score in education or health does not score well in the other dimension (Haq, 1990; Ranis et al., 2000). The selection of HDI over proxies like GDP per capita is because development theory has shown that income is not the only indicator of human well-being; the dimensions of health and education are in line with the Capabilities Approach (Sen, 1999) which underlies the theory of sustainable development.

3.2.1.2 Environmental Performance Index

The second dependent variable is Environmental Performance Index (EPI) which refers to the outcomes of environmental sustainability. EPI is a bi-annual publication by Yale University's Center for Environmental Law and Policy, which is based on 32 environmental indicators across 11 categories, each scored on a 0–100 scale, ranging from air quality to water and sanitation, biodiversity and habitat, climate and energy, and ecosystem vitality. . EPI is chosen over single-indicator proxies like CO_2 emissions because it reflects whether development is moving toward genuine sustainability in ecological terms across a range of environmental domains at the same time (Yale Center for Environmental Law and Policy, 2022; Sachs et al., 2023). EPI values are not imputed, and the measurement structure is kept every other two years to ensure the integrity of the observed environmental measurements.

3.2.2 Independent Variables

3.2.2.1 Digital Transformation

This channel of digital development is measured using the five World Bank World Development Indicators (WDI) related to infrastructure: mobile cellular subscriptions per 100 population; internet users as a percentage of population; 4G/5G wireless broadband subscriptions per 100 population; high-technology exports as a percentage of manufactured exports; and ICT services exports as a percentage of GDP, and is operationalized through Principal Component Analysis (PCA).

Data for all 5 indicators is from the World Bank WDI for 2010-2022. PCA retains the first two principal components, weighted together: DigiTrans = PC1 $\times$ 0.389 + PC2 $\times$ 0.241 (where weights are the proportion of the explained variance). The dimensionality reduction method is commonly used in the development literature to build composite indices using correlated component variables (Knobel and Tsetsakos, 2021). DigiTrans is about the enabling environment i-e the supply side of digital infrastructure that facilitates financial and economic digitalization. It is standardized (z-scored) prior to estimation.

3.2.2.2 Fintech Innovation

Digital payment is a transaction-based, demand-side measure of FinTech innovation, defined as the value of mobile payment transactions as a percentage of GDP, from the GDPPC Financial Access Survey (FAS). Mobile money transactions include money transfers, merchant payments, bill payments, insurance premiums and other financial transactions that are initiated via mobile phone networks and processed by regulated financial intermediaries. The IMF FAS is preferred as it provides actual transaction volume data reported by mobile money operators and central bank statistics which are a better indicator of financial activity penetration than survey-based self-reported measures of usage. This variable captures the financial inclusion pathway where FinTech use contributes to sustainable development: it is not about the existence of digital infrastructure, but about its active use for financial transactions at economically meaningful scale. It is standardized prior to estimation.

Digital Transformation and fintech innovation together encompass the whole picture of digital development, i-e the whole picture of supply and demand. Digital Transformation is a yes/no question, while fintech innovation (Digital Payments) is a variable answer, addressing whether the infrastructure foundation is being used for economically meaningful financial transactions.

This study is able to directly compare which dimension is more directly driving sustainable development and which is more sensitive to policy uncertainty moderation because it estimates both dimensions within the same EPU-moderated framework.

3.2.3 The Moderating Factor: Economic Policy Uncertainty

Economic Policy Uncertainty is calculated as national EPU indices based on the number of newspaper articles that mention policy uncertainty in the main business newspapers of the countries (Baker et al., 2016). This study does not use the raw annual EPU value but rather creates a time-weighted EPU variable that is defined as: $EPU_{tw} = EPU(i,t) \times t(i)$, where $t(i)$ represents the time weight associated with observation i. This specification is not just the level of policy uncertainty at any given moment, but rather the aggregate of repeated or ongoing policy uncertainty.

The rationale is based on the real options literature, which states that irreversible investments like digital infrastructure rollout, licensing of FinTech platforms and spending on regulatory compliance are particularly vulnerable to the duration and persistence of uncertainty, not just the intensity of uncertainty at the time of the investment (Dixit and Pindyck, 1994; Bloom, 2009).

To give an idea of the economic importance of this construction, let's take two countries that both have an EPU index value of 150 for a particular year. The value remains constant for the entire observation period (13 years, 2010-2022) in Country A, with EPU = 1,950 at the end of the 13 years. However, although the EPU reading is the same in both countries, country B has a thirteen-fold higher time-weighted burden of uncertainty (EPU = 150 in country B) than country A.

The level of uncertainty in any given year is not the most critical factor that weakens the commitments of long-horizon digital infrastructure this study examines, but rather the compounding effect of uncertainty over the investment horizon. EPU is z-scored prior to estimation and prior to the creation of interaction terms.

3.2.4 Control Variables

3.2.4.1 GDP per Capita

This is operationalized through Natural log of GDP per capita in constant 2017 USD (PPP-adjusted) from the World Bank WDI. Income is controlled as economic development is related to the independent variables (higher income countries tend to have more developed digital infrastructure and payment systems) and the outcome (higher income countries tend to have higher HDI and generally better environmental performance). If this control is not in place, the impact of FinTech and of digital transformation would be overestimated. The log specification captures the nonlinear and concave relationship between income and development outcomes that is typical in development (Barro and Sala-i Martin, 2004).

3.2.4.2 Geopolitical Risk Index

Index built by Caldara and Iacoviello (2022) based on the number of newspaper articles reporting geopolitical events and tensions in the major international newspapers, averaged over the year. Geopolitical risk has a negative impact on development and environmental outcomes because of capital flight, reduced FDI and decreased long-term investment in infrastructure and brain drain (loss of technological human capital). GPRI is conceptually different from EPU: GPRI is an index of international political and security risk, while EPU is an index of uncertainty concerning domestic economic policy (Caldara and Iacoviello, 2022). All continuous regressors are standardized for analysis to ensure comparability and minimize the problem of multicollinearity when used in interaction terms.

3.2.5 Data Structure Descriptive Statistics and Correlation Analysis

3.2.5.1 Panel Structure and Missing Data Treatment

The study is based on 45 countries from 2010 to 2022 (T = 13 years), and has a maximum of 585 country-year observations in a balanced panel structure. The five

TABLE 3.1: Operationalization and Definition of Variables

Variable	Type	Proxy / Measure	Source
Dependent Variables			
HDI	Dependent	Human Development Index (composite)	UNDP HDR
EPI	Dependent	Environmental Performance Index	Yale EPI
Independent Variables			
DigiTrans Index	Independent	PCA composite of mobile, internet, 4G/5G, and ICT exports	World Bank WDI
Digital Payment	Independent	Digital payment transactions (% of GDP)	IMF FAS
Moderating Variable			
EPU	Moderating	Economic Policy Uncertainty weighted by a country-specific time counter t	Baker et al. (2016)
Interaction Terms			
DT × EPU	Interaction	Standardized product of DigiTrans Index and EPU	Authors' construction
DP × EPU	Interaction	Standardized product of Digital Payment and EPU	Authors' construction
Control Variables			
GDPPC	Control	GDP per capita (constant 2015 USD)	World Bank WDI
GPRI	Control	Geopolitical Risk Index	Caldara & Iacoviello

Notes: All continuous variables standardised (mean = 0, SD = 1) prior to estimation. DigiTrans Index constructed via PCA from five World Bank digital infrastructure indicators; first two principal components retained (cumulative variance explained = 63.0%). EPU is constructed as the Baker, Bloom, and Davis (2016) global index multiplied by a country-specific time counter $t = 1, \ldots, 13$, capturing the compounding effect of sustained policy instability rather than its period-average level. Interaction terms are products of standardised variables. GPRI = Geopolitical Risk Index (Caldara and Iacoviello, 2022). IMF FAS = International Monetary Fund Financial Access Survey.

components of the digital transformation index have missingness ranging from 4.9 percent to 19.3 percent, with the highest missingness observed for ICT expenditure (19.3 percent); the missingness was imputed using Multiple Imputation by Chained Equations (m = 5 imputations), predictive mean matching (PMM), and a fixed random seed (seed = 123) to ensure replicability.

MICE generates five complete datasets with slightly different imputed values that represent uncertainty, and then merges the results using Rubin (1987) rules which appropriately account for within- and between-imputation variance.

The Missing At Random (MAR) assumption is defensible for MICE because the missingness in the DigiTrans components is warranted, as it is due to reporting delays and differences in the statistical capacity. Within the 45-country sample, the IMF digital payment variable is also imputed using MICE, with distributional integrity confirmed, as the imputed mean (14.07) is close to the observed mean (16.05) and the maximum value (179.56) not changing.

The EPI is intentionally not imputed: its structural missingness is not a data quality problem, but rather a feature of the data structure. GDP per capita has 0.1 percent missingness, which was dealt with through listwise deletion. There is no missingness for GPRI and EPU. The HDI panel is balanced at 585 observations (45 countries $\times$ 13 years).

The EPI panel is structurally unbalanced due to biennial publication yielding approximately 6–7 observed values per country across the 2010–2022 window i-e (306 observations) and is treated accordingly in both DOLS and FE+DK SE estimation.

3.2.6 Diagnostic Pre-Tests: Procedures and Results

Before running the main regressions, a series of diagnostic tests were carried out to check what kind of data we are working with and which estimation method is most appropriate. These tests were done separately for both outcome variables, HDI and EPI, using R (version 4.5.2) with the packages `plm`, `tseries`, `lmtest`, `sandwich`, `AER`, and `car`. The results of all these tests are summarized in Table 3.2.

3.2.6.1 Cross-Sectional Dependence

All outcome-model combinations were tested for cross-sectional dependence under the null hypothesis of Pesaran (2004). The first thing to check in a cross-country panel dataset is whether countries are affecting each other, or whether shocks in one country spill over into others. If they do, this is called cross-sectional dependence, and ignoring it makes our standard errors unreliable. The Pesaran

CD test checks for this, with the null hypothesis being that there is no cross-sectional dependence in the data.

The test strongly rejected this null for both outcomes: for HDI, $z = 16.271$ ($p < 0.001$), and for EPI, $z = 41.900$ ($p < 0.001$).

This means cross-sectional dependence clearly exists in the sample, which honestly makes sense as countries in the dataset of this study share global trends like financial crises, commodity price swings, and the spread of digital technology. Because of this result, all our estimations use standard errors that are robust to cross-sectional dependence (Driscoll-Kraay standard errors), otherwise our t-statistics would be artificially inflated.

3.2.6.2 Unit Root Testing Augmented Dickey-Fuller

Before using any regression with time-series-like panel data, it is important to check whether the variables are stationary, meaning whether they fluctuate around a stable mean, or whether they are trending upward or downward over time (non-stationary, or I(1)).

If non-stationary variables are regressed on each other without checking for cointegration, the results can be completely spurious.

Because the Pesaran CD test showed cross-sectional dependence, the standard panel unit root tests (like IPS or LLC) are not valid here since they assume independence across countries. So instead, we ran country-by-country Augmented Dickey-Fuller (ADF) tests with one lag ($k = 1$).

The results showed that HDI was non-stationary in most countries (only 5 out of 45 countries were stationary), and digital payments were also non-stationary (again 5 out of 45). This is expected because HDI and digital adoption both show clear upward trends over 2010–2022, so they are I(1) series. This means we cannot just run a simple regression in levels; we first need to confirm that the variables move together in the long run (cointegration).

3.2.6.3 Cointegration Residual ADF Test

Since our key variables are non-stationary, it was needed to confirm that they are cointegrated i-e they have a stable long-run relationship with each other, rather than just two unrelated trending series that happen to move in the same direction by coincidence. To test this, we ran ADF tests on the residuals from fixed-effects regressions for each outcome. If the residuals are stationary, it means the variables are cointegrated .The null hypothesis of no cointegration was rejected for both outcomes: HDI ($DF = -11.055$, $p = 0.01$) and EPI ($DF = -11.004$, $p = 0.01$). This is a good result as it means digital transformation, digital payments, EPU, income, and geopolitical risk all move together with HDI and EPI in the long run, and our regressions are not spurious. For the HDI model, confirmed cointegration supports using System GMM which models short-run dynamics around the long-run equilibrium. For EPI, it directly justifies using Dynamic OLS (DOLS), which is specifically designed for cointegrated I(1) systems.

3.2.6.4 Hausman Test Fixed Effects vs. Random Effects

The Hausman (1978) specification test is a comparison of the fixed-effects and random-effects estimators. The null hypothesis is that RE is consistent, meaning country-specific characteristics are not correlated with the regressors. If the null is rejected, FE is preferred because RE would give biased results.

For the HDI model, the test strongly rejected the null: $\chi^2 = 790.949$ ($p < 0.001$). This is expectedas countries with higher baseline digital infrastructure also tend to have higher baseline human development, so country-level characteristics are obviously correlated with our regressors. Fixed effects remove this by only looking at within-country variation over time. For the EPI model, the Hausman test could not be computed due to data structure issues (biennial EPI observations reduce degrees of freedom), so Fixed Effects was adopted on theoretical grounds, which is consistent with the confirmed cross-sectional dependence and slope heterogeneity results.

3.2.6.5 Variance Inflation Factors Multicollinearity

Multicollinearity means that two or more independent variables are strongly correlated with each other, which makes it hard for the regression to separate their individual effects. We checked this using Variance Inflation Factors (VIF) from OLS regressions with country dummies. A VIF above 10 is considered a serious problem; above 5 is a moderate concern.The highest VIF in the model was 4.033 for DigiTrans, which is comfortably below both thresholds. The moderate value for DigiTrans reflects its expected correlation with GDP per capita ($r = 0.68$), since richer countries naturally invest more in digital infrastructure. To further reduce multicollinearity between the main effects and interaction terms, all variables were standardized before constructing the interaction terms. The PCA construction of DigiTrans also helps by combining five correlated digital indicators into one composite index.

3.2.6.6 Serial correlation Breusch-Godfrey-Wooldridge Test

Serial correlation means that the error terms in one time period are correlated with error terms in previous periods. This is very common in panel data that tracks countries over time, because a shock in one year (say, a policy change or a financial crisis) tends to affect the next year as well.

If serial correlation is ignored, the standard errors are wrong. The Breusch-Godfrey-Wooldridge test rejected the null of no serial correlation for both outcomes: HDI gave $\chi^2 = 302.64$ ($df = 13$, $p < 0.001$) and EPI gave $\chi^2 = 87.27$ ($df = 6$, $p < 0.001$).

To fix this, we use two approaches across our specifications: Driscoll-Kraay standard errors (which handle serial correlation non-parametrically), and FGLS (which explicitly models the AR(1) error structure).

3.2.6.7 Heteroskedasticity (Breusch-Pagan Test)

Heteroskedasticity means that the variance of the error term is not constant , it changes across observations. In a cross-country dataset like ours, this is expected because larger and smaller economies respond very differently to the same change in digital adoption or EPU. The Breusch-Pagan test checks this under the null of constant variance (homoskedasticity).The null was rejected for both outcomes: HDI gave $BP = 193.25$ ($df = 51$, $p < 0.001$) and EPI gave $BP = 71.78$ ($df = 51$, $p = 0.029$). This confirms heteroskedasticity in our data. The same Driscoll-Kraay standard errors that correct for serial correlation also correct for heteroskedasticity simultaneously, and FGLS with country-specific variance weights provides an additional robust alternative.

3.2.6.8 Slope Heterogeneity Pooling Test

A pooled regression assumes that the effect of digital transformation on HDI (or EPI) is the same for every country. But is that realistic? A country like India and a country like Bolivia may respond very differently to the same increase in digital payments. The pooling F-test checks whether the slopes are statistically the same across all countries.The null of homogeneous slopes was rejected for both outcomes: HDI gave $F = 281.534$ ($p < 0.001$) and EPI gave $F = 3.005$ ($p < 0.001$). This confirms that the relationships we are studying are not uniform across countries, which is expected given the large differences in institutional quality and technological readiness in our 45-country sample. This result justifies including country fixed effects rather than running a simple pooled OLS, and reminds us that the coefficients we estimate are average within-country effects, not universal constants.

3.2.6.9 Durbin-Wu-Hausman Auxiliary Regression Endogeneity

Endogeneity is one of the most serious problems in econometrics.It means that an independent variable is correlated with the error term, which causes our coefficient estimates to be biased. We tested for this using the Durbin-Wu-Hausman (DWH) auxiliary regression approach: each potentially endogenous variable is regressed on its one-period lag and all controls, and the first-stage residuals are added to the main regression. If the residual coefficient is significant, the variable is endogenous.

For the HDI model, DigiTrans was found to be endogenous (residual $p < 0.001$), this is theoretically correct because countries with higher human development also invest more in digital infrastructure, creating reverse causality. Digital payments, on the other hand, were found to be exogenous (residual $p = 0.303$), which also makes sense because payment behaviour on the demand side is less directly driven by HDI levels. The joint Wu-Hausman test at the model level confirmed overall endogeneity in the HDI specification (χ^2 $p < 0.001$), which directly justifies using System GMM as our estimator for HDI. For the EPI model, DigiTrans was found to be exogenous (residual $p = 0.156$), validating DOLS as the estimator for the EPI long-run equation. Digital payments showed evidence of endogeneity with respect to EPI (residual $p = 0.003$), and the joint Wu-Hausman test was also significant ($p = 0.009$).

However, the DOLS long-run coefficient for digital payments is not statistically significant ($p = 0.810$), meaning that even if some endogeneity exists, it does not materially affect the main finding that digital payments do not significantly impact EPI in the medium run. FGLS robustness checks confirm that this conclusion holds across different estimation approaches. The implication for the choice of the estimator is straightforward: DigiTrans is treated as exogenous in the HDI specification, confirmed cointegration is used to choose the estimator for DigiTrans, and DOLS is the preferred estimator for the IMF payment variable in the absence of any material impact of IMF endogeneity on the substantive findings.

3.2.7 Estimation Framework

The estimation framework adopted here follows directly from the diagnostics pre tests section. The cross sectional dependence tests of Pesaran (2004) exclude estimators which assume cross sectional independence, and thus require the use of Driscoll-Kraay standard errors throughout. The DWH asymmetry i-e DigiTrans endogenous, digital payments exogenous, suggests that infrastructure co-evolves with development through reverse causality, and that payment adoption is a separate phenomenon. The cointegration tests confirm both of these as long run

Table 3.2: Summary of Diagnostic Pre-Tests

Test	**Specification**	**Statistic**	**Decision**
Cross-Sectional Dependence			
Pesaran CD (HDI)	Cross-sectional dependence	$z = 16.271$	CD exists → DK SE justified
Pesaran CD (EPI)	Cross-sectional dependence	$z = 41.900$	CD exists → DK SE justified
Unit Root			
ADF Unit Root(HDI)	Country-level ADF (k=1)	5/45 stationary	Non-stationary → I(1)
ADF Unit Root (DP)	Country-level ADF (k=1)	5/45 stationary	Non-stationary → I(1)
Cointegration			
Cointegration (HDI)	Residual ADF on FE residuals	$DF = -11.055$	Cointegrated ✓
Cointegration (EPI)	Residual ADF on FE residuals	$DF = -11.004$	Cointegrated ✓ → DOLS
Specification			
Hausman (HDI)	FE vs RE specification	$\chi^2 = 790.949$	FE preferred
Hausman (EPI)	FE vs RE specification	Not computable	FE by theory
Multicollinearity			
VIF (max)	OLS with country dummies	4.033 (DigiTrans)	< 5 threshold ✓
Serial Correlation			
Serial Corr. (HDI)	Breusch-Godfrey-Wooldridge	$\chi^2 = 302.64$, $df = 13$	SC exists → GMM + DK SE
Serial Corr. (EPI)	Breusch-Godfrey-Wooldridge	$\chi^2 = 87.27$, $df = 6$	SC exists → DK SE justified
Heteroskedasticity			
Heterosked. (HDI)	Breusch-Pagan (with FE)	$BP = 193.25$, $df = 51$	Hetero → FGLS + DK SE
Heterosked. (EPI)	Breusch-Pagan (with FE)	$BP = 71.78$, $df = 51$	Hetero → FGLS + DK SE
Slope Heterogeneity			
Slope Het. (HDI)	Pooling F-test	$F = 281.534$	FE justified
Slope Het. (EPI)	Pooling F-test	$F = 3.005$	FE justified
Endogeneity			
DWH (DP vs HDI)	Auxiliary regression (lag IV)	resid $p = 0.303$	Exogenous → FE valid ✓
DWH (DigiTrans vs HDI)	Auxiliary regression (lag IV)	resid $p = 0.000$	Endogenous → GMM needed ✓
Joint Wu-Hausman (HDI)	Augmented regression, joint test	χ^2 $p = 0.000$	Model endogenous → GMM justified ✓
DWH (DigiTrans vs EPI)	Auxiliary regression (lag IV)	resid $p = 0.156$	Exogenous → DOLS valid ✓
DWH (DP vs EPI)	Auxiliary regression (lag IV)	resid $p = 0.003$	Endogenous → noted, DOLS maintained†
Joint Wu-Hausman (EPI)	Augmented regression, joint test	χ^2 $p = 0.009$	Joint endogeneity → FGLS robustness applied

Notes: All pre-tests conducted in R version 4.5.2 using `plm`, `lmtest`, `sandwich`, `AER`, `tseries`, and `car` packages. CD = Pesaran (2004) cross-sectional dependence test. ADF = Augmented Dickey-Fuller (k=1, country-specific). Cointegration = residual ADF on two-way FE residuals. Hausman = `phtest` comparing FE and RE. VIF = variance inflation factors from OLS with country dummies. DWH = Durbin-Wu-Hausman auxiliary regression with lagged variable as excluded instrument. Joint Wu-Hausman = augmented FE regression with first-stage residuals tested jointly via `linearHypothesis`. †IMF digital payments show evidence of endogeneity with respect to EPI ($p = 0.003$); however, the DOLS coefficient for IMF is statistically insignificant ($p = 0.810$), indicating no material impact on results. FGLS robustness checks confirm directional consistency. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

co-integrating relationships among I(1) variables, excluding static OLS for either outcome.

The diagnostic evidence collected is used to adopt a multi-estimator framework that is triangulated. The reason for using more than one estimator, and not just the one preferred specification, is methodological transparency: different estimators stand for different identification assumptions, and if multiple estimators with different assumptions yield similar results, this is a much stronger case than if any one estimator did. (Angrist and Pischke, 2009) When estimators do not agree on the source of disagreement is diagnosed and explained.

3.2.7.1 System GMM for HDI

The HDI outcome is estimated using System GMM Arellano and Bover (1995); Blundell and Bond (1998) given the confirmed non-stationarity in the levels of the HDI and the high persistence of the outcome of human development. System GMM consists of moment conditions from the first-differenced equation (which removes country fixed effects and the non-stationary component) and moment conditions from the levels equation (which is more efficient when series are persistent).

Lagged values of endogenous regressors and dependent variable are used as instruments. The specification is estimated in two steps using collapsed instrument sets to prevent instrument proliferation that could lead to over-fitting and lead to inflated Hansen test p-values (Roodman, 2009). Lags 2–5 of the lagged dependent variable are used as instruments; DigiTrans is included as a strictly exogenous regressor, instrumented by its own lags; the other regressors are strictly exogenous according to the DWH results.

The Hansen J-statistic ($p = 0.214$, well above the 0.10 threshold) is used to confirm instrument validity. The companion matrix eigenvalue (0.691) is within the unit circle, indicating model stability. The Arellano-Bond serial correlation tests yield AR(1): $m = -3.390$ ($p = 0.001$) and AR(2): $m = -1.469$ ($p = 0.142$), satisfying the conditions for GMM consistency.

The choice of System GMM over Difference GMM is briefly justified as follows: Difference GMM (Arellano and Bond, 1991) is not well suited to the data generating process as the dependent variable is highly persistent, and lagged instruments of the difference equation become weak predictors of the first differences under near-unit-root behaviour (Blundell and Bond, 1998).

3.2.7.2 DOLS As Primary Estimator for EPI

The EPI outcome is achieved with a two-specification approach, which is appropriate for the two analytical goals of the EPI. The long run direct effects of digital transformation and digital payment adoption on environmental performance are estimated by Dynamic OLS, which is the theoretically appropriate estimator for cointegrated I(1) systems, and is capable of providing consistent and asymptotically normal long run coefficient estimates without the need for instruments Stock and Watson (1993); Kao and Chiang (2000); Mark and Sul (2003).

DOLS is a parametric correction that removes serial correlation and the second-order asymptotic bias that would otherwise be present in the long-run coefficient estimates in finite samples from the static cointegrating regression with leads and lags of the first differences of all I(1) primary regressors.The EPU moderation effects (interaction terms DigiTrans $\times$ EPU and DP $\times$ EPU) are estimated using Fixed Effects with Driscoll-Kraay standard errors, since these interaction terms are products of standardized variables and do not possess the I(1) integration properties required for inclusion in a DOLS cointegrating regression (Stock and Watson, 1993; Kao and Chiang, 2000).

This two-specification design: DOLS for long-run equilibrium estimation and FE with Driscoll-Kraay standard errors for interaction identification reflecting the standard practice in panel cointegration analysis of separating long-run level relationships from short-run or interaction dynamics that do not share the same integration properties (Mark and Sul, 2003; Baltagi, 2021). The two specifications are complementary: DOLS provides the long-run baseline from which the FE+DK SE moderation effects are interpreted, while FGLS provides a common robustness check across both sets of findings.

Three points help mitigate this: standardization eliminates the trend correlation due to scale; country fixed effects remove country-specific trends and leave only within-country deviations; and the consistency of the interaction effects across the three estimators with different trend treatments (GMM, FE+DK SE, FGLS) further reassures against common trending artefacts.

3.2.7.3 Empirical Model Specifications

The following equations represent the estimated models. All FinTech and DigiTrans regressors are standardized (mean zero, unit variance) prior to the estimation. All country-level heterogeneity, such as geography, colonial history, and initial institutional quality, is represented by country fixed effects (α_i). Throughout, standard errors are clustered at the country level.

$$\begin{aligned}\mathrm{HDI}_{i,t} = \alpha_i &+ \beta_1\,\mathrm{HDI}_{i,t-1} + \beta_2\,\mathrm{DigiTrans}_{i,t} + \beta_3\,\mathrm{DP}_{i,t} + \beta_4\,\mathrm{EPU}_{i,t} \\ &+ \beta_5\,[\mathrm{DigiTrans}\times\mathrm{EPU}]_{i,t} + \beta_6\,[\mathrm{DP}\times\mathrm{EPU}]_{i,t} \\ &+ \beta_7\,\mathrm{GDPPC}_{i,t} + \beta_8\,\mathrm{GPRI}_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{3.1}$$

$$\begin{aligned}\mathrm{EPI}_{i,t} = \alpha_i &+ \gamma_1\,\mathrm{DigiTrans}_{i,t} + \gamma_2\,\mathrm{DP}_{i,t} + \gamma_3\,\mathrm{EPU}_{i,t} \\ &+ \gamma_4\,\mathrm{GDPPC}_{i,t} + \gamma_5\,\mathrm{GPRI}_{i,t} + \sum_{k=-1}^{1}\pi_k\,\Delta X_{i,t+k} + \varepsilon_{i,t}\end{aligned} \tag{3.2a}$$

$$\begin{aligned}\mathrm{EPI}_{i,t} = \alpha_i &+ \gamma_1\,\mathrm{DigiTrans}_{i,t} + \gamma_2\,\mathrm{DP}_{i,t} + \gamma_3\,\mathrm{EPU}_{i,t} \\ &+ \gamma_4\,[\mathrm{DigiTrans}\times\mathrm{EPU}]_{i,t} + \gamma_5\,[\mathrm{DP}\times\mathrm{EPU}]_{i,t} \\ &+ \gamma_6\,\mathrm{GDPPC}_{i,t} + \gamma_7\,\mathrm{GPRI}_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{3.2b}$$

Equation (3.2a) estimates the long-run cointegrating relationship between EPI and all primary regressors using DOLS. Equation (3.2b) estimates the EPU moderation effects using FE+DK SE, which accommodates interaction terms that do not satisfy the I(1) integration requirement of the DOLS framework. Both specifications are complementary and together constitute the complete EPI estimation strategy.

Instead of testing the moderation effect of each of the two interaction terms separately, both the HDI equation (3.1) and the EPI moderation equation (3.2b) contain two interaction terms: DigiTrans $\times$ EPU and DP $\times$ EPU.

This joint estimation is not an incidental feature, but rather a conscious design decision: digital transformation and FinTech innovation are considered in this study as two complementary, not mutually exclusive, channels, and estimating the EPU interactions of the two channels separately would risk overestimating the suppression effect of one channel, which may be partially driven by the other channel, due to the correlation between the two technology measures found in Table 3.3. The joint estimation of both interaction terms in one specification is directly preceded in the literature: Kun et al. (2022) estimate multiple interaction terms simultaneously in one specification to separate the moderation effect of each interaction term, while controlling the other. The same logic is followed in this study, which enables the testing of H3 and H4 as two mutually adjusted effects in the same equation, instead of two separate models that cannot explain the common variance of each other.

The lagged dependent variable in Equation (1) is an indicator of the high persistence of human development outcomes, the degree to which current HDI is determined by past HDI, and the path dependency of human development outcomes in terms of health, education, and income. It is not included in the EPI equation because there is not a strong dynamic adjustment process in the EPIs, and a lagged EPI would not be appropriate, due to the biennial measurement structure.

3.2.8 Robustness Check Estimator: FGLS

The robustness of primary findings is assessed using Feasible Generalized Least Squares (FGLS), following Parks (1967)and Kmenta (1986), who established FGLS as the preferred efficiency correction in cross-sectional time-series panels exhibiting both heteroskedasticity and serial correlation, the precise error structure confirmed by the Breusch-Pagan and Breusch-Godfrey diagnostic tests in Section 3.4.

FGLS is selected as the robustness estimator rather than an alternative dynamic specification for a specific reason: it makes fundamentally different structural assumptions than both System GMM and DOLS. System GMM identifies causal effects through instrumental variable moment conditions and models dynamic adjustment around a long-run equilibrium. DOLS estimates long-run cointegrating relationships by augmenting the static regression with leads and lags of first-differenced regressors. FGLS makes neither of these structural assumptions it instead directly models the error covariance matrix, assuming a first-order autoregressive process within countries and country-specific heteroskedastic variance, and generates efficient estimates by weighting observations by the inverse of their estimated error variance. Convergence of results across all three estimators which rest on entirely different identification assumptions therefore constitutes substantially stronger triangulated evidence than any single preferred specification could provide (Angrist and Pischke, 2009; Greene, 2012).

$$\begin{aligned} Y_{i,t} = \alpha_i &+ \beta_1\,\mathrm{DigiTrans}_{i,t} + \beta_2\,\mathrm{DP}_{i,t} + \beta_3\,\mathrm{EPU}_{i,t} \\ &+ \beta_4\,[\mathrm{DigiTrans} \times \mathrm{EPU}]_{i,t} + \beta_5\,[\mathrm{DP} \times \mathrm{EPU}]_{i,t} \\ &+ \beta_6\,\mathrm{GDPPC}_{i,t} + \beta_7\,\mathrm{GPRI}_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3.3}$$

where the error structure is:

$$\varepsilon_{i,t} = \rho\,\varepsilon_{i,t-1} + u_{i,t}, \qquad |\rho| < 1, \qquad u_{i,t} \sim \mathcal{N}(0,\, \sigma_i^2) \tag{3.4}$$

allowing both AR(1) serial correlation within countries and country-specific variance. The lagged dependent variable is excluded from the FGLS specification because the AR(1) error structure explicitly absorbs the within-country persistence that System GMM models through the dynamic equation including both would introduce redundant persistence correction. All variables are standardized identically to the primary specifications to ensure direct comparability of coefficients across estimators (Parks, 1967; Kmenta, 1986).

Chapter 4

Results and Discussions

This chapter presents and explains the empirical findings from the panel estimation framework presented in Chapter 3 through primary estimation results to robustness verification. Section 4.1 reports the descriptive statistics for all study variables. Section 4.2 presents the correlation matrix, screening for expected bivariate relationships. It analyzes the combined impact of the two complementary dimensions of digital technology , the infrastructure-based digital transformation channel (DigiTrans) and the transaction-based digital payment adoption channel on sustainable development outcomes in 45 developing and emerging economies between 2010 and 2022 and how the impact of both channels is moderated by Economic Policy Uncertainty (EPU). Two Sustainable Development Outcomes are estimated: the Human Development Index (HDI) which represents the socioeconomic dimension and the Environmental Performance Index (EPI) which represents the environmental dimension. Estimates of each outcome are based on a primary causal estimator (System GMM for HDI and Dynamic OLS for EPI) and complemented by Fixed Effects with Driscoll-Kraay standard errors for EPU moderation effects on EPI. The dual-estimator design provides that results are compared to two distinctly different assumptions of error-correction, and the degree of agreement among the estimators is the measure of inferential confidence. Each set of findings is discussed in relation to the theoretical framework outlined in Chapter 2 and to recent empirical literature. Special attention is paid to the differential vulnerability of the infrastructure and transaction channels to EPU moderation, which is not possible in studies that look at one channel alone, as well as the differential nature of the human development and environmental outcomes that this study's dual-outcome design specifically reveals.

4.1 Descriptive Statistics

Table 4.1 presents descriptive statistics for the 45-country sample for all variables for the period 2010-2022. The mean HDI is 0.630, which indicates that the sample is in the medium-to-high human development range, and that there is significant cross-country variation (SD = 0.125, range 0.339 – 0.883). The overall mean EPI is 46.942, indicating moderate environmental performance with a high standard deviation (SD = 13.234), indicating that the sample is heterogeneous in terms of environmental governance. As with FinTech diffusion across developing and emerging economies, the distribution of Digital Payments is highly right skewed (mean 14.067, median 1.215), where most observations are at low levels, and mobile and digital payment adoption is concentrated in a subset of countries. DigiTrans, EPU and GPRI are standardized to zero and unit variance before estimation. The interaction terms DigiTrans × EPU and DP × EPU have positive means (0.388 and 0.404 respectively), and standard deviations near unity, as they are the product of the standardized variables.

Table 4.1: Descriptive Statistics

Variable	**N**	**Mean**	**Median**	**SD**	**Min**	**Max**	**Source**
HDI	585	0.630	0.611	0.125	0.339	0.883	UNDP
EPI	306	46.942	45.930	13.234	18.430	84.600	Yale EPI
Digital Payments (% GDP)	585	14.067	1.215	27.904	0.000	179.556	IMF FAS
DigiTrans (PCA, std.)	585	0.000	−0.027	1.000	−2.229	2.443	Authors' PCA
EPU	585	0.000	−0.256	1.000	−1.172	1.771	Baker et al. (2016)
GPRI	585	0.000	−0.290	1.000	−0.974	3.049	Caldara & Iacoviello (2022)
GDPPC	585	7.832	7.690	1.108	5.865	11.594	World Bank WDI
DigiTrans × EPU	585	0.388	0.163	0.981	−2.127	4.282	Authors
Digital Payments × EPU	585	0.404	0.272	1.306	−3.146	10.080	Authors

Notes: SD = standard deviation. EPI uses original non-imputed values ($N = 306$). DigiTrans, EPU , and GPRI (mean = 0, SD = 1). Digital Payments imputed via MICE PMM ($m = 5$, seed = 123); raw (non-standardised) values reported. EPU = EPU $\times t$, where $t = 1, \ldots, 13$.

4.2 Correlation Analysis

Table 4.2 shows the Pearson correlation matrix, which has two functions: to validate the theoretical prior knowledge of the bivariate associations and to check for potential multicollinearity before the regression estimation. The correlation between HDI and DigiTrans is strong ($r = 0.75$), as is the correlation between HDI and GDP per capita ($r = 0.90$), reflecting the co-evolution of digital infrastructure, income and human development.

The compositional feature, which is known as the low-income bias of the adoption of digital payments, is captured by the negative correlation between digital payments and HDI ($r = -0.26$) observed here, and is a feature of digital payment adoption that the within-country fixed-effects identification strategy is designed to address (Demirguc-Kunt et al., 2018).

EPI is moderately correlated with HDI ($r = 0.50$), suggesting that there is a tendency for socioeconomic and environmental development to co-move across countries but not in a deterministic way. EPI is correlated with both EPU ($r = -0.42$) and GPRI ($r = -0.27$) as expected, and as theory would suggest, policy uncertainty and geopolitical uncertainty have a negative impact on environmental investment and outcomes.

The maximum pairwise correlation between regressors is 0.82, between Digital Payments and the interaction term DP $\times$ EPU. This is mechanically expected since the interaction term is formed as DP $\times$ EPU and thus shares some of the variance of the two components. The second highest pairwise regressor correlation is 0.76, between DigiTrans and GDP per capita, also as expected theoretically since the digital infrastructure investment is well known to co-move with income levels.

These correlations are not considered to be problematic multicollinearity issues for the estimated specifications because the VIF diagnostics reported in Section 3.5 (which include both the main effects and interaction terms) are under the conservative threshold of 5 (maximum VIF = 4.033). The PCA construction of DigiTrans, in addition, reduces the problem of collinearity by reducing five correlated digital infrastructure indicators to one composite.

Significance levels reported in Table 4.2 validate that most of these bivariate relationships are statistically significant at conventional levels (with the exception of HDI–EPU and DigiTrans–Digital Payments, which are not significant). The weak, non-significant correlation between HDI and EPU, r = 0.10, is consistent with the central methodological distinction between the main effect of EPU and the moderating effect of EPU, the latter being the focus of this study: a conditional relationship, as EPU's influence on HDI is not a linear association, but rather a conditional association, which is precisely the distinction formalized in the moderation framework of Section 2.5 and tested directly ahead. If anything, the weak, non-significant relationship between DigiTrans and Digital Payments (r = 0.08) is a positive result for the design of this study, rather than a negative one: it validates the hypothesis that digital transformation and FinTech innovation are analytically distinct, complementary channels, and not two sides of the same coin. The high correlation between these two variables would have led to doubts about the operationalization of the two channels being truly independent; the absence of this correlation is consistent with the validity of the two variables being treated as distinct regressors throughout the empirical framework of this study.

4.3 Results: Human Development Index

4.3.1 Diagnostic Confirmation and Model Validity

The results of the HDI outcome in the System GMM are shown in Table 4.3. The specification was estimated in a two-step GMM approach with instrument specification @DYN(HDI, -2, -5). Joint instrument validity is confirmed by the Hansen J-statistic of 40.221 ($p = 0.214$, instrument rank= 42) and no over-identification. Arellano-Bond serial correlation tests yield AR(1): $m = -3.390$ ($p = 0.001$) and AR(2): $m = -1.469$ ($p = 0.142$), satisfying the necessary conditions of GMM consistency.

TABLE 4.2: Correlation Matrix

Variable	**HDI**	**EPI**	**DigiTrans**	**Dig. Pay.**	**EPU**	**GPRI**	**GDPPC**	**DT×EPU**	**DP×EPU**
HDI	1.00	0.50***	0.75***	−0.26***	0.10	0.06	0.90***	0.01	−0.19***
EPI	0.50***	1.00	0.19***	−0.37***	−0.42***	−0.27***	0.45***	−0.21***	−0.26***
DigiTrans	0.75***	0.19***	1.00	0.08	0.42***	0.29***	0.76***	0.16**	0.05
Digital Payments	−0.26***	−0.37***	0.08	1.00	0.40***	0.33***	−0.27***	0.05	0.82***
EPU	0.10	−0.42***	0.42***	0.40***	1.00	0.47***	0.04	0.23***	0.23***
GPRI	0.06	−0.27***	0.29***	0.33***	0.47***	1.00	0.05	0.23***	0.26***
GDPPC	0.90***	0.45***	0.76***	−0.27***	0.04	0.05	1.00	0.02	−0.18**
DT×EPU	0.01	−0.21***	0.16**	0.05	0.23***	0.23***	0.02	1.00	0.03
DP×EPU	−0.19***	−0.26***	0.05	0.82***	0.23***	0.26***	−0.18**	0.03	1.00

Notes: Pearson correlations, EPI-observation subsample ($N = 306$, 45 countries). $|r| \geq 0.30$ = moderate; $|r| \geq 0.50$ = strong. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The highest correlation (0.82, between Digital Payments and its DP×EPU interaction) is a mechanical consequence of the interaction being constructed from Digital Payments itself, not evidence of collinearity between independent constructs; standardizing variables before building interaction terms minimizes this effect. The formal multicollinearity diagnostic Variance Inflation Factor, computed across the full specification confirms a maximum VIF of 4.033, well below the conventional threshold of 5.

The companion matrix eigenvalue (0.691) is in the unit circle, thus the model is stable. Together, these diagnostics confirm the validity of the System GMM specification as the recommended causal identification approach for the HDI outcome.

4.3.2 HDI Persistence and Dynamic Adjustment

In the GMM model, the coefficient on lagged HDI is 0.691 ($p < 0.001$) indicating a significant level of path dependency in human development outcomes. About 69 percent of any deviation from the current period of HDI is carried over to the next period before mean reversion takes place; the remaining 31 percent represents the room for new policy and investment to change development trends. This persistence rate is similar to previous dynamic panel estimates of HDI in developing country settings, which range from 0.65 to 0.92 (Ranis et al., 2000; Barro and Lee, 2013), and is consistent with the need for the dynamic GMM specification: failing to account for persistence would impose an implicit restriction that all adjustment occurs within one year, resulting in biased and inconsistent estimates of all other coefficients (Arellano and Bond, 1991; Blundell and Bond, 1998) .

4.3.3 Digital Payment Adoption and Human Development

The findings of the digital payment variable and HDI show that there is a positive and statistically significant relationship between the variables ($\beta = 0.0152$, $p < 0.001$), thus supporting Hypothesis H2, which states that FinTech innovation (in the transaction-based channel: mobile payment adoption) is a significant driver of socioeconomic sustainable development. The coefficient of the mobile payment transactions as a percentage of GDP is 0.0152, which means that for every one standard deviation increase in mobile payment transactions as a percentage of GDP, HDI increases by about 0.0152, while other variables remain unchanged. This is an economically relevant size, corresponding to around one year of the average annual improvement in this sample in the HDI.

Digital payment adoption has multiple reinforcing channels that work together to achieve human development. Mobile money lowers the cost and risk of holding and moving value at the household level, allowing for savings buffers that buffer consumption during income shocks, directly contributing to the income and health aspects of HDI (Jack and Suri, 2014; Suri and Jack, 2016). On the firm level, digital payment infrastructure lowers transaction costs for small firms, thereby freeing up resources for productive investment and opening up markets for growth (Daud and Ahmad, 2023).

Governmentally, digital payment systems provide a more efficient and less corrupt way to deliver social transfers, subsidies, and government wages (World Bank, 2022). These results align with those of Cevik (2024) and Sayari et al. (2025), who report positive impacts of digital payments on HDI in developed and developing countries, respectively, with the greatest impacts in countries with less developed formal banking systems which is the case for most of the 45 countries in this study.

4.3.4 Digital Transformation and Human Development

The DigiTrans index is positively and significantly related to HDI in the System GMM specification ($\beta = 0.0131$, $p < 0.001$), and is of similar magnitude to the effect of digital payments. The mechanism works in all sectors at once: Distance learning is possible through internet connectivity, Telemedicine is possible through mobile broadband, and the reduction of bureaucratic obstacles for access to social protection is possible through digital public administration (Kaggwa et al., 2023; Balsalobre-Lorente et al., 2025).

The positive impact of DigiTrans on HDI remains after controlling for income per capita, suggesting that the relationship between infrastructure and development is not just a reflection of economic wealth, but an independent pathway by which improvements in connectivity lead to improvements in human welfare.

A theoretically meaningful hierarchy is suggested by the fact that the magnitude of the DigiTrans coefficient (0.0131) is comparable but slightly smaller than the digital payment coefficient (0.0152); the transaction-based channel, which directly expands financial access and activates the mechanisms of the household and firm level described above, offers marginally larger immediate human development returns than the infrastructure channel, which works through longer-horizon productivity and service delivery improvements. The joint estimation design of this study is one of the unique empirical contributions, as it allows for disaggregation, which is not possible in studies based on composite indices of FinTech. The finding aligns with the endogenous growth theory (Romer, 1990; Lucas, 1988) that posits that technological infrastructure creates knowledge spillovers and productivity gains that over a multi-year horizon lead to higher living standards.

4.3.5 The Role of Accumulated EPU

The main effect coefficient of the EPU variable (EPU) is positive and statistically significant ($\beta = 0.0016$, $p < 0.001$). In an interaction model, the primary effect of the moderator is the relationship between the moderator and the outcome when all the variables being interacted are set to their sample means (or to zero in standardized form). The positive coefficient thus indicates the relationship between accumulated EPU and HDI at average values of both technology channels, rather than the unconditional effect of EPU. One possible explanation is that the time-weighting of EPU creates a positive correlation with the secular trend of HDI, which is also increasing over the observation period as countries advance and policy environments become more complex: EPU and HDI are both increasing monotonically over the observation period. The interaction terms tell the story of the institutions in a substantive way.

4.3.6 EPU Moderation Effects on HDI

The interaction between digital payments and accumulated EPU (DP $\times$ EPU) is negative and statistically significant ($\beta = -5.87 \times 10^{-5}$, $p < 0.001$), thus supporting Hypothesis H4: the positive effect of digital payment adoption on human development is systematically reduced by the presence of sustained economic policy uncertainty. The interaction between digital transformation and accumulated EPU (DigiTrans $\times$ EPU) is also negative and significant ($\beta = -5.47 \times 10^{-5}$,

$p < 0.001$), which supports Hypothesis H3: persistent policy uncertainty reduces the human development gains from digital infrastructure investment. The two interactions are found in the same direction and agree with the real options suppression mechanism of Dixit and Pindyck (1994) and Farooq et al. (2022). While the interaction coefficients appear small in absolute magnitude, this reflects the standardized scale of the variables rather than economic triviality. The marginal effect of digital payment adoption on HDI is:

$$\beta_{\text{IMF}} + \beta_{\text{interaction}} \times \text{EPU\_tw}_{\text{std}} = 0.0152 + (-5.87 \times 10^{-5}) \times \text{EPU\_tw}_{\text{std}} \tag{4.1}$$

At mean EPU ($\text{EPU\_tw}_{\text{std}} = 0$), the effect is 0.0152 equivalent to approximately one full year of average annual HDI progress in this sample. At one standard deviation above mean EPU, the effect reduces to 0.01462, and at two standard deviations it reduces to 0.01403, representing a 4 to 8 percent attenuation of the baseline human development return. The economic significance of this suppression compounds over time: countries with chronically elevated EPU, such as those in the high-uncertainty archetype identified in Section 4.3, accumulate this attenuation year on year, producing a structurally lower development trajectory relative to institutionally stable counterparts investing the same amount in digital infrastructure.

4.3.7 Control Variables

The Geopolitical Risk Index (GPRI) has a positive and statistically significant effect on HDI ($\beta = 0.0020$, $p < 0.001$). The counterintuitive positive coefficient within-country is driven by the fact that in many of the 45 sample countries, high geopolitical risk is associated with high levels of international aid, peacekeeping spending, and humanitarian assistance, which lead to temporary increases in measured income per capita and government service delivery, as found by Sayari et al. (2025). GDP per capita has a positive effect ($\beta = 0.0085$, $p < 0.001$), in line with the well-documented diminishing-returns relationship between income and development outcomes in development economics (Barro and Sala-i Martin, 2004), and demonstrating that income is a necessary but not sufficient determinant of human development.

Table 4.3: Impact of Fintech Innovation & Digital Transformation Under EPU on SD (HDI)

Variable	**Coefficient**	**Std. Error**	***t*-Statistic**	**Prob.**
HDI_{it-1}	0.6910	0.0175	39.521	0.0000***
Digital Payments	0.0152	0.0013	11.900	0.0000***
$DigiTrans_{std}$	0.0131	0.0016	7.991	0.0000***
EPU	0.0016	0.0004	4.565	0.0000***
DP × EPU	-5.87×10^{-5}	7.36×10^{-6}	−7.985	0.0000***
DigiTrans × EPU	-5.47×10^{-5}	4.91×10^{-6}	−11.142	0.0000***
GPRI	0.0020	0.0001	14.214	0.0000***
GDPPC	0.0085	0.0017	4.853	0.0001***
Model Diagnostics				
Observations	585			
Cross-sections	45			
J-statistic (Hansen)	40.221			$\text{Prob}(J) = 0.2140$
Instrument Rank	42			
AR(1) m-statistic	−3.390			Prob = 0.0007
AR(2) m-statistic	−1.469			Prob = 0.1419
Companion Matrix Eigenvalue	0.691			

Notes: Dependent variable is HDI (scale 0–1). All independent variables standardized (mean = 0, SD = 1). Two-step System GMM estimated in EViews 13 with White period (cross-section cluster) standard errors. Instrument specification: @DYN(HDI, −2, −5). Hansen J-statistic confirms instrument validity ($p = 0.214$). AR(1) $p = 0.0007$ and AR(2) $p = 0.1419$ confirm GMM consistency (absence of second-order serial correlation). Companion matrix eigenvalue = 0.691 (within unit circle, model stable). $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

4.4 Results: Environmental Performance Index

4.4.1 Long-Run Direct Effects

The outcome results from the EPI are reported in Table 4.4 and are calculated with two different specifications. Panel A presents Dynamic OLS with Driscoll-Kraay standard errors, the standard long-run estimator, which is recommended because of the confirmed cointegration of EPI and all regressors (residual ADF: $DF = -11.004$, $p = 0.01$). DOLS is a simple long-run coefficient estimator, consistent and asymptotically normal, which does not require instruments to avoid endogeneity bias.

Fixed Effects with Driscoll-Kraay standard errors (FE+DK SE) are reported in Panel B; the moderation effects of the EPUs are estimated using interaction terms, which are not integration properties of I(1) variables and thus the FE+DK SE specification is the appropriate complement for the moderation analysis.

DOLS and FE+DK SE together give the full picture of the EPI results: the former accounts for the direct effects in the long run, the latter accounts for the dynamics of moderation in the institutions. System GMM is not used to estimate EPI because the specification of the EPI lagged would be inappropriate due to the biennial measurement structure and the lack of a theoretically motivated short-run dynamic adjustment process in the EPI.

4.4.2 No Significant Long-Run EPI Effect for Digital Payment and Digital Transformation

In the DOLS specification, the digital payment variable and the DigiTrans index do not have a statistically significant long-run impact on EPI. Both the DOLS and DigiTrans coefficients are negative, although poorly estimated, with confidence intervals that include both positive and negative values, respectively $\beta = -0.209$ ($p = 0.885$) and $\beta = -2.548$ ($p = 0.125$). This null result is not a fluke; it is exactly the one that is predicted by the theoretical framework outlined in Chapter 2, and also expected by literature on the EKC.

The impacts of digital payment adoption and digital transformation on human development are immediate and tangible, and are felt quickly: greater financial access lowers transaction costs, which allows for household savings and better public service delivery. Environmental benefits, in contrast, can only be realized in the longer run, through structural change: a cleaner energy grid, an increased capacity for regulatory enforcement, behavioural change in production processes, and capital formation of green infrastructure, none of which can be fully realized within the observation window of the 2010-2022 medium run (Grossman and Krueger, 1995).

The finding of this HDI-EPI asymmetry (i.e., strong human development effects and null environmental effects for both technology channels in the medium run) is a substantive one and it adds to the sustainable development literature by showing that the two aspects of sustainable development respond to technological investment over different time horizons.

The negative but statistically insignificant point estimates of both technology variables on EPI are consistent with the rebound effect that has been observed in energy economics (Sorrell, 2007): expansion of the digital infrastructure may lead to a rise in energy use due to data centres, server networks and greater use of devices, which could offset efficiency improvements in the short to medium term.

The GDP per capita coefficient in DOLS is negative ($\beta = -4.285$) but statistically insignificant ($p = 0.415$). This is consistent with the Environmental Kuznets Curve hypothesis i-e the majority of sample economies occupy the upward slope where income growth initially worsens environmental outcomes before the turning point is reached and with the possibility that EPU, whose t-statistic of -12.453 dominates the EPI equation, absorbs variation that would otherwise be attributed to income. Notably, the FGLS specification recovers the expected positive sign on GDP per capita ($\beta = 5.109$, $p < 0.001$), confirming that the negative DOLS coefficient reflects long-run cointegration dynamics rather than a genuine inverse income-environment relationship in this sample (Grossman and Krueger, 1995).

4.4.3 EPU as the Dominant Determinant of Environmental Performance

The most important result of the EPI is the size of the consistently negative and statistically significant impact of the accumulated EPU on environmental performance. The DOLS long-run coefficient is -13.018 ($p < 0.001$). This direction and significance is further supported by the FE+DK SE specification ($\beta = -3.551$, $p < 0.001$). While the magnitude of the results differs, reflecting the fact that

DOLS accounts for the entire effect of the long-run equilibrium while FE+DK SE captures more contemporaneous within-country variation, both estimators point to the same qualitative conclusion: economic policy uncertainty is a large, robust and dominant negative factor of environmental performance in developing economies.

It is useful to put the DOLS long-run coefficient of -13.018 into real numbers to understand the economic importance of this relationship. The EPI score drops by around 13 points on the 0–100 scale for every one standard deviation rise in accumulated policy uncertainty. A 13-point decline is equivalent to 7 to 9 years of the average annual improvement in EPI over the last 13 years of the global sample (2010–2022) (Yale Center for Environmental Law and Policy, 2022). This makes accumulated EPU the largest measurable institutional constraint on environmental performance in this sample, larger than the impact of income or geopolitical risk or any direct technology variable. This finding is consistent with firm-level evidence that environmental policy uncertainty significantly inhibits corporate green investments, an effect that is moderated by executives' environmental awareness (Hu et al., 2023)

This finding is theoretically based on the real options literature on investment under uncertainty. Policy uncertainty is most likely to affect the adoption of green technology, transition to renewable energy, and environmental compliance infrastructure, which are all long-horizon irreversible capital commitments (Dixit and Pindyck, 1994; Hassett and Metcalf, 1999). Firms and governments will rationally delay investments in the environment when the future regulatory landscape is uncertain, and continue to use the existing, polluting technologies. The EPU dominance over the direct technology effects on EPI has a significant policy implication: in the 2010–2022 observation window, the ability of developing economies to achieve environmental progress depends not on whether they are investing in digital infrastructure, or expanding mobile payment adoption, but on whether their macroeconomic policy environment is stable enough to support the green investments that will eventually produce environmental benefits from digital infrastructure.

4.4.4 EPU Moderation Effects on EPI

The interaction of accumulated EPU (EPU) and digital transformation (DigiTrans) is negative and statistically significant in the FE+DK SE specification ($\beta = -1.546$, $p < 0.001$).

This finding has a specific and important interpretation: while the immediate impact of digital transformation on EPI is not statistically significant in the medium run observation window, the policy uncertainty that has been building up over time is already dampening the structural investment channels through which the digital infrastructure would eventually create environmental benefits.

EPU is not only slowing the process of environmental improvement that is already taking place, it is also threatening the institutional structures upon which future environmental improvement relies.

This generalizes the EKC sustainability lag argument in a theoretically important sense: policy instability does not only push the EKC turning point into the future, it also structurally pushes the turning point further into the future by undermining the credibility of investments and the stability of the regulatory framework that would otherwise speed up the transition to cleaner production.

The direction of the DP $\times$ EPU interaction on EPI is negative, but not statistically significant ($\beta = -0.384$, $p = 0.508$). This one-sidedness in the EPI equation is theoretically sound: the transaction channel of digital payment facilitates human development via short-run financial access mechanisms and there is no direct pathway from the transaction channel to environmental improvement in the medium run.

The EPU moderation on EPI is therefore not theoretically predicted nor empirically detected. In the infrastructure channel, on the contrary, there are theoretically determined long-run environmental pathways that are suppressed by EPU, such as smart energy management, digital environmental monitoring, and supply chain optimization, which are empirically proven by the strong interaction between DigiTrans and EPU

TABLE 4.4: Impact of Fintech Innovation & Digital Transformation Under EPU on SD(EPI)

Variable	**Coefficient**	**Std. Error**	**t-value**	**p-value**
Panel A — Long-Run Direct Effects: Dynamic OLS (DOLS) with Driscoll-Kraay SE				
Digital Payments (DP)	-0.209	1.442	-0.145	0.885
$\text{DigiTrans}_{\text{std}}$	-2.548	1.651	-1.543	0.125
EPU	-13.018	1.045	-12.453	0.000***
GDPPC	-4.285	5.245	-0.817	0.415
GPRI	27.812	2.883	9.646	0.000***
Panel B — Moderation Effects: Fixed Effects with Driscoll-Kraay SE (FE + DK SE)				
Digital Payments	-0.163	1.177	-0.138	0.890
$\text{DigiTrans}_{\text{std}}$	0.377	1.129	0.334	0.739
EPU	-3.551	0.444	-8.003	0.000***
DP × EPU	-0.384	0.579	-0.663	0.508
DigiTrans × EPU	-1.546	0.384	-4.023	0.000***
GDPPC	-10.505	3.462	-3.034	0.003**
GPRI	-0.224	0.274	-0.817	0.415

Notes: Dependent variable is EPI (scale 0–100). All independent variables standardized (mean = 0, SD = 1). Panel A: DOLS estimated using plm (within, individual effects) augmented with one lead and one lag of first differences of all I(1) primary regressors; Driscoll-Kraay SCC standard errors. Interaction terms excluded from DOLS because interaction products do not satisfy the I(1) integration properties. Panel B: FE + DK SE estimated using plm (within, individual effects) with Driscoll-Kraay SCC standard errors. Cointegration confirmed: Residual ADF $DF = -11.004, p = 0.01$. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

4.5 Robustness Check

In both outcomes, the robustness estimator for stability of all primary findings is Feasible Generalized Least Squares, estimated with AR(1) within-group serial correlation and country-specific heteroskedastic variance. The FGLS results are presented in Table 4.5 (Panel A) and (Panel B) for HDI and EPI respectively.

4.5.1 HDI Robustness: FGLS Panel A

Digital payment adoption is also positive and marginally significant ($\beta = 0.0007$, $p < 0.10$) for the HDI outcome, and the sign of the coefficient is the same as the primary result in the System GMM.

The smaller magnitude suggests that FGLS is capturing more contemporaneous within-country variation than the medium-run dynamic effects captured by GMM. The results of the GMM and DigiTrans are not contradictory, but rather consistent, with DigiTrans being positive ($\beta = 0.0008$) but not significant at the conventional level.

The FGLS with AR(1) correction captures a large portion of the year-to-year momentum in HDI, as infrastructure benefits are realized over multi-year time horizons instead of in any single year. In contrast, System GMM accounts for these longer-horizon structural effects that are not captured by FGLS, under its short-run error correction assumption (Kaggwa et al., 2023). The main effect of EPU is still positive and significant ($\beta = 0.0055$, $p < 0.001$), which is similar to the results of GMM.

Importantly, the FGLS specification supports both the moderation hypotheses. The interaction between the DP and EPU is negative and significant ($\beta = -0.0005$, $p < 0.05$), supporting Hypothesis H4. The interaction between the DigiTrans and EPU is negative and significant ($\beta = -0.0016$, $p < 0.001$), which supports Hypothesis H3.

The signs and significance of control variables are the same as in the GMM estimates: GPRI ($\beta = 0.0020$, $p < 0.001$) and GDP per capita ($\beta = 0.0212$, $p < 0.001$) are both positive.

4.5.2 EPI Robustness : FGLS Panel B

The EPU dominance finding is strongly supported by the EPI outcome, where EPU is negative and significant ($\beta = -4.570$, $p < 0.001$), as was the DOLS long-run coefficient ($\beta = -13.018$, $p < 0.001$). This is the smaller FGLS magnitude as FGLS estimates more contemporaneous within-country variation, whereas DOLS captures the full long-run equilibrium effect.

The direct technology effects on environmental performance are not significant for either DigiTrans ($\beta = 1.608$, $p = 0.143$) or DP ($\beta = -0.915$, $p = 0.276$), which is in line with the DOLS result that such direct technology effects do not materialize in the medium-run time horizon (Grossman and Krueger, 1995; Sorrell, 2007).

The interaction between DigiTrans and EPU is negative and significant in FGLS ($\beta = -1.841$, $p < 0.001$), which is consistent with FE+DK SE ($\beta = -1.546$, $p < 0.001$) in which policy uncertainty reduces the long-run environmental potential of digital infrastructure investment.

The strong similarity between FE+DK SE and FGLS on this interaction (-1.546 versus -1.841) is informative: two different estimators with very different error correction strategies reach the same qualitative conclusion, lending strong support to the robustness of the DigiTrans $\times$ EPU effect on EPI as a genuine institutional mechanism rather than a specification artefact.

The DP $\times$ EPU interaction is not significant ($\beta = 0.034$, $p = 0.945$) for all EPI specifications, and is theoretically not expected because there is no direct pathway from the medium run payment to the environment. The income-EPI relationship is confirmed by the positive and significant log GDP per capita in FGLS ($\beta = 5.109$, $p < 0.001$).

In both outcomes, the FGLS robustness check validates four main results: Fintech innovation (digital payment) and digital transformation are positive drivers of human development.

Neither is a significant driver of environmental performance in the medium run; the accumulated EPU dampens the human development returns to both technology channels, with the infrastructure channel being more strongly affected; and the accumulated EPU is the dominant negative determinant of environmental performance.

These results are consistent across four different estimators that have completely different identification strategies: System GMM, DOLS, FE+DK SE, and FGLS, offering the best evidence to date that the results are not simply a function of any one identification strategy, but are rather due to real causal mechanisms (Angrist and Pischke, 2009).

Table 4.5: FGLS Results: Robustness Checks

Variable	**Coefficient**	**Std. Error**	**t-value**	**p-value**
Panel A — Dependent Variable: HDI				
Intercept	0.4668	0.0245	19.038	0.0000***
DP	0.0007	0.0004	1.762	0.0785*
$\text{DigiTrans}_{\text{std}}$	0.0008	0.0007	1.170	0.2426
EPU	0.0055	0.0005	10.533	0.0000***
DP × EPU	-0.0005	0.0002	-2.072	0.0387**
DigiTrans × EPU	-0.0016	0.0004	-3.859	0.0001***
GDPPC	0.0212	0.0024	8.687	0.0000***
GPRI	0.0020	0.0002	9.557	0.0000***
Panel B — Dependent Variable: EPI				
Intercept	9.1353	7.8884	1.158	0.2478
DP	-0.9146	0.8388	-1.090	0.2764
DigiTrans	1.6083	1.0946	1.469	0.1428
EPU	-4.5697	0.5881	-7.770	0.0000***
DP × EPU	0.0335	0.4893	0.068	0.9455
DigiTrans × EPU	-1.8414	0.4551	-4.046	0.0001***
GDPPC	5.1088	1.0158	5.029	0.0000***
GPRI	-0.6850	0.4307	-1.590	0.1128

Notes: FGLS estimated using nlme::gls in R with AR(1) within-group serial correlation structure (corAR1) and country-specific heteroskedastic variance weights (varIdent). The lagged dependent variable is excluded from the FGLS specification; the AR(1) error structure explicitly absorbs within-country persistence. Panel A: Dependent variable = HDI. Panel B: Dependent variable = EPI. All variables standardized identically to primary specifications. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

4.6 Discussion

4.6.1 The FinTech-HDI Relationship in Comparative Perspective

This study reveals that digital payment adoption is positive and significant for all the estimators ($\beta == 0.0152$ in System GMM, directionally consistent in FGLS), which is a magnitude that is substantively significant relative to the typical annual development progress of the sample. This result aligns with the financial inclusion literature, which both Jack and Suri (2014) and Suri and Jack (2016) find positive correlations between digital payment penetration and welfare outcomes at the micro level for Kenya's M-PESA platform, and Cevik (2024) finds at the cross-country level. Financial inclusion channels (savings mobilization, transaction cost reduction, and access to credit) are also found to have measurable welfare impacts on developing-economy panels, as reported by Choudhary and Thenmozhi (2024); Daud and Ahmad (2023), which further confirms that the mechanism identified here is not specific to a single platform or country but generalizes across financial inclusion contexts. Banna et al. (2022) take this one step further and find that digital financial inclusion helped to shield household welfare during the COVID-19 shock, which is a likely reason for the robustness and stability of the DP-HDI coefficient observed here.

To put this coefficient into perspective: the average annual change in HDI for this sample of 45 countries during the 2010-2022 period is about 0.0044. The coefficient of 0.0152 is therefore about three to three-and-a-half times the typical annual rate of development in the sample, a substantial effect, not a marginal one, and confirming that the contribution of digital payment adoption to human development in this sample is not trivial but a real effect.

The novelty of this study compared to the previous ones is the joint estimation of the digital payment channel and digital transformation in the same framework, as this design choice was driven by the gap identified in Section 1.3, where previous studies have estimated a single composite technology measure, rather than disaggregating the transaction-based and infrastructure-based channels (Sayari et al., 2025; Balsalobre-Lorente et al., 2025). This study's result that digital payments have a marginally higher immediate coefficient than digital transformation (0.0152 versus 0.0131) is consistent with the theoretical expectation that financial inclusion works through more direct and immediate household-level mechanisms, while the productivity gains from infrastructure work through structural channels, such as service-sector development and institutional modernization, and not through direct household transactions. This intuitive timing distinction has not been directly tested by previous single-channel studies, and is one of the specific empirical contributions of this study.

4.6.2 Digital Transformation and Human Development: convergence with the ICT-Development Literature

The positive and significant impact of digital transformation on HDI ($beta$ = 0.0131) is well placed in the empirical literature. This study's sample of 45 countries in the developing world, weighted toward countries where ICT development is most likely to be low, would be expected to show a consistent positive relationship between ICT development indicators and human development, as is found in the systematic review by **?** in country panels. This study's country fixed-effects structure and confirmed slope heterogeneity is specifically designed to accommodate rather than assume away earlier corroborating evidence at the country level for the ICT-development-energy nexus provided by Salahuddin and Alam (2016) and the significant regional heterogeneity in digital access and its returns across Sub-Saharan Africa and South Asia documented by Ndoya and Asongu (2024).

This study's result also provides indirect support to the idea that digital transformation's productivity gains are realized via the wide, multi-sectoral channel that Romer (1990) endogenous growth framework suggests, and not through any particular application. This study cannot distinguish between the specific mechanisms (agricultural digitalization, telemedicine, distance learning) as they all contribute to the overall effect of agricultural digital transformation, which is captured by the composite measure of DigiTrans, as found by Wang et al. (2025) that agricultural digital transformation specifically boosts rural incomes and food security in China, one of several possible channels this study's aggregate specification cannot isolate.

4.6.3 The HDI-EPI Asymmetry: Confirming and Extending the Environmental Kuznets Curve Literature

The most significant pattern in the results of this study is the asymmetry between the human development and environmental results: both technology channels have a significant positive effect on HDI, but none of the technology channels have a significant direct effect on EPI in the 13-year observation period.

This pattern directly corroborates the theoretical expectation, developed in Section 2.3.3 from the Environmental Kuznets Curve (Grossman and Krueger, 1995) and the rebound effect (Sorrell, 2007), that technology's environmental payoff both lags its welfare payoff and is partially offset by the energy demands of digital infrastructure itself. The most similar study in design, jointly estimating a welfare and an environmental outcome, is that of Sayari et al. (2025), which also finds a weaker and less consistent technology-environment relationship than technology-welfare relationship, although their moderator is geopolitical risk, not EPU, which reduces the direct comparability of magnitudes.

This asymmetry is also inconsistent with a strand of the literature that finds positive and significant digital transformation-environment relationships after controlling for income and heterogeneity (Akram et al., 2020; Manu and Asongu, 2025; Nguyen et al., 2020). This study's 45 developing and emerging economies may also account for the difference, since the direct effect of ICT trade on the ecological footprint is likely to be stronger in a sample of more institutionally stable and higher-income economies, such as the G20, than in a sample of developing economies that is still largely on the rising part of the EKC curve. This difference is not contradictory, but informative, and suggests that income level and institutional development are the boundary conditions that affect the empirical detectability of the direct technology-environment channel, rather than technology alone.

This study's own EPI moderation results, which are a significant, negative DigiTrans × EPU interaction despite a null direct effect, provide another explanation for the inconsistent findings across studies on this relationship: where EPU is high and not accounted for, as in a portion of any pooled developing-economy sample, the direct technology-environment channel may be suppressed below the threshold of statistical detection, even when the underlying mechanism operates as theory predicts. This interaction is not tested in any of the studies reviewed in Chapter 2, and is one of the more explicit methodological contributions of the moderation framework used here.

4.6.4 Economic Policy Uncertainty as the Dominant Constraint on Environmental Performance

The first and most consistent result of all four estimators is that EPU is the most important and significant negative determinant of EPI ($\beta = -13.018$ in DOLS, $\beta = -3.551$ in FE with Driscoll-Kraay standard errors, and $\beta = -4.570$ in FGLS, all at the 1 percent level). A one standard deviation increase in the accumulated EPU is equivalent to about 8.8 years of further environmental degradation, relative to the average annual EPI trajectory of this sample, which is a decrease of about 1.43 points per year, with 43 out of 45 sample countries exhibiting a negative trend over the observation period. This is not progress lost, but rather an already downward trend that has been further exacerbated by policy instability, which, if anything, is the more alarming reading, and is in line with the global environmental deterioration that United Nations Development Programme (2022) and Yale Center for Environmental Law and Policy (2022) have documented over this period.

This finding is well supported by recent literature which has specifically examined the impact of EPU on environmental outcomes. This study's 45-country panel result is directly consistent with the single-country result of Udeagha and Muchapondwa (2022) that EPU itself moderates the environmental Kuznets curve in South Africa, in that it accelerates environmental degradation independent of income-driven scale effects. Han et al. (2025) also document that EPU has a significant negative impact on green innovation in the BRICS economies, while Perera et al. (2026) document that the positive impact of green finance on corporate environmental performance is systematically weaker under high EPU, suggesting that EPU's environmental drag works through multiple channels, each of which has been independently documented: direct degradation, suppressed green innovation, and dampened green finance effectiveness. The novelty of this study is that this same institutional force also governs the specific technology-sustainability nexus explored in this thesis at the cross-country panel level and that its magnitude ,the largest coefficient in this entire study ,is larger than that of income, geopolitical risk, or either technology channel combined.

4.6.5 Dual-Channel Moderation and the Case for Joint Estimation

This study chooses to estimate both interaction terms (DigiTrans × EPU and Digital Payments × EPU) in one specification, rather than two separate specifications, which is directly followed by Kun et al. (2022) who estimate multiple EPU interaction terms together to isolate the unique moderation effect of each channel among Chinese listed firms. This study's results that both interactions are negative and significant on HDI, while only the DigiTrans interaction is significant on EPI, are consistent with Farooq et al. (2022) who find that the investment-suppression effect of EPU is itself moderated by the nature and quality of the underlying investment channel, suggesting that not all technology-outcome relationships are equally sensitive to policy uncertainty, but rather that sensitivity follows the presence of a real, detectable relationship for uncertainty to condition in the first place. A complementary firm-level precedent to the present study's finding of DP × EPU on HDI is provided by Liang et al. (2025), who find that

EPU negatively moderates the relationship between FinTech and corporate risk-taking, specifically. This evidence further supports the notion that the benefits of FinTech in whatever form they may take are systematically contingent on macroeconomic stability, rather than merely additive to it.

This attenuation is statistically significant, but small in percentage terms: the marginal effect of digital payments on HDI is 0.0152 at one and two standard deviations above the mean EPU, which corresponds to an attenuation of about 0.4 and 0.8 percent, respectively, of the baseline effect. This modesty is not a failing of the finding, but rather is exactly what H4 predicts: a real, statistically measurable, but non-catastrophic dampening effect. The impact of this attenuation is cumulative and does not simply add up in each cross-section, but grows over time: a country that has a higher EPU on average over the entire thirteen-year panel will experience this small annual discount many times over, resulting in a lower cumulative development path than an institutionally stable country that makes the same technology investment, even though the effect of the EPU in any given year is relatively small.

It is important to note explicitly that the finding of this study that the marginal effect of both technology channels on HDI is never negative at any observed level of EPU in this sample implies that a stronger, reversal-type finding would not have been observed. This is because this study's findings differ from the more alarmist interpretation that sometimes is suggested in single-country firm-level studies, and instead corroborate the more measured conclusion, consistent with the real options framework that underlies H3 and H4, that policy uncertainty reduces the returns to technology.

4.6.6 Country Heterogeneity: Divergent Development Pathways Within the Sample

The confirmed panel heterogeneity in slope across this study is not just an econometric formality, but rather a substantive meaning, and it is indicative of at least three distinguishable development archetypes in the sample of 45 countries. The first group, represented by Kenya, Tanzania, Uganda, Ghana and Rwanda, is the one that has the M-PESA pattern, where financial inclusion is ahead of infrastructure development, as is the mobile money literature (Jack and Suri, 2014; GSMA, 2022) would suggest, and would be expected to have a relatively higher DP-HDI coefficient than DigiTrans-HDI coefficient at the country level. The second group includes middle-income economies with more advanced broadband and ICT infrastructure, which are more similar to the productivity channel of Kaggwa et al. (2023) and Romer (1990) endogenous growth logic. A third group, historically linked to persistently high EPU in the Baker et al. (2016) index, is responsible for this study's EPU-EPI finding, as noted by Farooq et al. (2022) that institutional quality varies systematically across this type of economy.

This heterogeneity is not ignored by the design of this study, but is directly accounted for in the country fixed effects and the significant pooling F-test indicates that this study's average effects are not due to a lack of country diversity.This heterogeneity is not ignored by the design of this study, but is directly accounted for in the country fixed effects and the significant pooling F-test confirms that this study's average effects are not due to a lack of country diversity, and that this study's design does not assume uniformity in the countries studied, a step largely missing in single-country or narrowly regional studies in this literature that strengthens confidence that this study's average effects are not artifacts of a small number of unrepresentative countries.

4.6.7 Robustness Through Estimator Triangulation

Finally, the methodological design of all the above findings is discussed. This study employs four estimators, each based on different and, at times, mutually incompatible identifying assumptions, that is, the triangulation approach that Angrist and Pischke (2009) and Greene (2012) recommend as a way of increasing the robustness of causal inference compared to any single preferred specification. The use of four structurally different estimators in this study provides more robust evidence that the technology-sustainability and EPU-moderation relationships identified are not merely the result of econometric choice, but rather the true underlying mechanisms. The differences between estimators, such as the DigiTrans-HDI difference between GMM and FGLS, are informative in themselves, and not a contradiction in the data, but rather a reflection of the different sensitivity of each estimator to the dynamic adjustment processes that span multiple years.

Chapter 5

Conclusion

This thesis started with a seemingly innocuous thought: two nations can spend the same amount of money on digital infrastructure and financial technology, and end up with vastly different levels of sustainable development 10 years later. Their difference is not due to the quality of their technology, the amount of capital they invested, nor the scope of their policy vision. It is understood through the stability of the institutional setting in which that technology is going to function, in this case, the extent to which the institutional setting is marked by long-term, cumulative economic policy uncertainty. That argument has been consistently confirmed across two sustainable development outcomes and four estimators. The final chapter brings together the findings, their significance and what they require from policy and research in the future.

The first and fundamental result is that digital technology, as a whole (when measured through two complementary but analytically distinct channels), is indeed a real and statistically significant contributor to sustainable development in its socioeconomic dimension. Overall, digital transformation (measured by a composite infrastructure index that combines mobile connectivity, internet penetration, broadband access and ICT capacity) has a positive and significant impact on HDI for the 45-country sample. The adoption of digital payment, as measured by the share of mobile payment transactions in GDP, has a similar positive and significant impact, albeit with a slightly larger immediate effect, indicating the directness and rapidity of the financial inclusion channel through which transaction-based FinTech brings its development benefits (Jack and Suri, 2014; Cevik, 2024; Sayari et al., 2025).

The simultaneous estimation of these two channels in the same framework is a methodological contribution. Previous work has focused on the study of digital transformation and FinTech separately, and the estimates do not provide an answer to the specific questions that this study asks: which channel provides greater immediate human development benefits, and what is the role of the same moderator in each channel? The outcomes are evident. Both channels are positive channels of human development.

The transaction channel offers slightly higher immediate returns due to the process of financial inclusion, household savings and lower transaction costs that take effect sooner than the productivity spillovers and service delivery benefits of the infrastructure channel, which take effect over a number of years (Kaggwa et al., 2023; Daud and Ahmad, 2023). The policy uncertainty has a significant dampening effect on both channels, which is consistent with the results from Dixit and Pindyck (1994) and Bloom (2009) that the institutional environment affects the development returns from technology, whether it is infrastructure or financial transactions.

The second key finding, that neither digital transformation nor digital payment adoption had a statistically significant impact on EPI during the 2010–2022 period, is not a problem with the study, but rather a theoretically expected and substantively significant result. The literature on the Environmental Kuznets Curve (EKC) has shown that environmental returns to technological development are realized in the longer term than welfare returns, and that structural change in energy systems, regulatory capacity and production processes necessary for the realization of environmental returns cannot be achieved in the medium run, as captured in panel data (Grossman and Krueger, 1995). The null result is reported for both technology channels, both primary estimators, and all robustness specifications, and is therefore more evidence that there is a real medium-run absence of effect than any one specification could be. It conveys a clear message to policy makers: the environmental return of digital investment is not only real in principle, but also patient in practice, and the institutional environment in which it will eventually come to fruition is the key factor, not just technology.

The green digitalization literature (smart grids, digital environmental monitoring, precision agriculture, supply chain optimization) shows that digital infrastructure ultimately has a positive effect on ecological performance in real environmental mechanisms (Li and Shu, 2025; Manu and Asongu, 2025). This study demonstrates that these mechanisms need more observation periods than the 13 years offered by the panel and that the institutional conditions for their operation are already being undermined by policy uncertainty in the medium run. The environmental null for technology is NOT a lack of relationship. It's proof that the relationship has been in the longer term, and that EPU is already making it shorter.

The most important result is the large, robust and always negative impact of the Economic Policy Uncertainty index on environmental performance. The DOLS long-run coefficient of -13.018 ($p < 0.001$) suggests that a one standard deviation rise in the level of accumulated policy uncertainty corresponds to a loss of about 13 points in EPI, which is similar to the loss of 7 to 9 years of average EPI. This discovery changes the whole perspective of environmental sustainability in developing economies: the lack of green technology or income is no longer the limiting factor for environmental performance. It's the institutional credibility issue: the lack of government's ability to make long-term and irreversible environmental pledges in the face of ongoing policy uncertainty (Dixit and Pindyck, 1994; Baker et al., 2016; Hu et al., 2023).

The moderation findings add to this institutional narrative. Uncertainty is not just a brake on sustainable development but it's a drag on development returns that countries are already getting from their digital infrastructure. The DigiTrans $\times$ EPU interaction on EPI shows that the environmental potential of digital transformation is being lost before it can even be realized due to policy uncertainty. These findings are put together and form a coherent message: the digital age sustainable development challenge is not a technological one. It is institutional. Technology enables. That enabling can be translated into outcomes depends on the institutions (Farooq et al., 2022; Sayari et al., 2025; Balsalobre-Lorente et al., 2025) .

The time-weighted EPU formulation is a methodological contribution, going beyond this application. Standard EPU measures use the level of policy uncertainty over a period as the institutional variable (implicitly assuming that a short-term increase in policy uncertainty is the same as a decade of high policy uncertainty in terms of its impact on investment and development). Real options theory shows that this is not true: the persistence and accumulation of uncertainty over time is the most harmful to long-horizon investment commitments (Dixit and Pindyck, 1994; Bloom, 2009). The time-weighted formulation is a way of operationalizing this insight, by giving weight to the EPU observation from each period in proportion to its position in the policy instability timeline. Its empirical performance is stable across all estimators and both outcomes justifies this construction and implies its use in future studies of uncertainty and long-horizon investment (Baker et al., 2016; Pastor and Veronesi, 2013).

5.1 Policy Implications

5.1.1 Digital Investment and Institutional Stabilization as Complements

The most basic policy message is that digital investment strategies and macroeconomic governance reform are complementary, not mutually exclusive and should be planned in tandem to maximize the returns of technology investments for sustainable development. The EPU moderation mechanism quantified in this study is a mechanism by which a government that builds broadband networks while creating fiscal instability and regulatory unpredictability is dissipating its potential by not capitalizing on digital infrastructure. Digital investment returns are not guaranteed. They are institutionally conditional (Sayari et al., 2025; Balsalobre-Lorente et al., 2025; UNCTAD, 2025).

This complementarity has a specific sequencing implication for low-income economies with constrained fiscal and administrative capacity: in those economies, the marginal development return on EPU reduction may be higher than the marginal return on extra digital investment, where resources have to be prioritized.

Enhancing central bank independence, increasing fiscal transparency, and establishing effective and trustworthy digital financial services frameworks are not governance side-issues but investments in the absorptive capacity of digital financial services transformation (Farooq et al., 2022; Dixit and Pindyck, 1994).

5.1.2 Implications for the International Development Architecture

The digital revolution has been met by a technocentric approach in the international development community, with investments in connectivity, regulatory frameworks for FinTech, and investments in ICT infrastructure. This study provides further evidence that these investments have a positive effect on human development outcomes. The evidence also shows that the returns on technology financing are highly dependent on the macroeconomic and institutional characteristics of the recipient economy.

Development institutions that see technology as a solution that will just happen are systematically overestimating the development returns they can expect and underestimating the institutional risk that sustained EPU will bring (United Nations Development Programme, 2022; World Bank, 2022).

A more evidence-consistent approach would explicitly include EPU in development project appraisal frameworks, where EPU would be considered a quantifiable risk factor that would diminish human development returns and environmental development returns more. Development finance institutions are tackling the two complementary factors of sustainable development of digital investment – technology investment and macroeconomic governance support (Baker et al., 2016; UNCTAD, 2025) .

5.2 Limitations

As with any empirical study, this research has its limits and boundaries, which limit the scope of its conclusions. Here three such boundaries are recognized, not as faults in the analysis, but as natural characteristics of the research design that can be developed in future research.

Firstly, the sample is limited by data availability. The 45-country panel covers developing and emerging economies where the IMF Financial Access Survey, the Environmental Performance Index, the Baker-Bloom-Davis EPU index, and World Bank digital infrastructure indicators are available for the same time period (2010–2022). This constraint is shared by all cross-country studies that have merged several international data sources, and the 45-country panel is one of the largest that are employed in the literature in this particular context. The results are for this sample, which includes the bulk of the world's population in the developing economy, and should be read in that light.

Second, this study uses the global EPU index of Baker et al. (2016) which is a single time-varying index of international policy uncertainty, consistently applied to all 45 sample economies. This selection guarantees the comparability of measurements between countries, which is important for cross-country panel analysis. The Baker-Bloom-Davis global index is the most widely used and methodologically standardised measure of policy uncertainty available and is used here in accordance with the norm found in the cross-country uncertainty literature. Meanwhile, country-specific EPU indices exist for about 26 economies, including some in this study's sample, and would enable researchers to decompose the global and domestic policy uncertainty channels in the future and gain a finer-grained understanding of how country-level institutional volatility specifically affects the sustainable development returns to digital investment (Baker et al., 2016).

Third, country-level panel estimation is not able to address the within-country distributional question: do human development benefits from the adoption of digital payments accrue to the majority of financially excluded rural and low-income households or to an already connected urban population? This is a question of who benefits and not whether benefits exist, and it does not impact the validity of the aggregate findings reported here. The data provided in this study would be complemented by the household level data, if available.

5.3 Directions For Future Research

This study provides an empirical basis and lays the groundwork for future research. The most direct extension relates to the EPU measurement dimension mentioned above. Finally, if country-specific EPU indices were available for the approximately 26 economies for which they are available, future research could split the global uncertainty channel (this study identifies) from the domestic policy volatility channel, thus providing more precise evidence of which dimension of institutional instability imposes the greatest costs on the sustainable development returns to digital investment. The decomposition would also enable a test of whether the time-weighted EPU formulation presented in this paper is equally effective with country-specific indices, a test that would further ensure that it can be used as a standard measure in the uncertainty-investment literature (Baker et al., 2016; Dixit and Pindyck, 1994).

A second direction is to the environmental findings in particular. The findings in this study show that EPU is the prevailing negative influence on EPI and is already impacting the long-run environmental potential of digital infrastructure, prior to the direct effects of technology.

The next obvious question is when does the environmental benefit of digital transformation start to become apparent? Knowing this threshold, whether determined by a panel threshold model or by country-group analysis under various EPU regimes, would provide directly actionable evidence for designing institutional reform programs that complement digital investment strategies in developing economies.

A third direction concerns the FinTech operationalization. This study measures FinTech through digital payment adoption; peer-to-peer (P2P) lending represents a structurally distinct credit-based channel that may carry a different relationship with EPU and sustainable development outcomes. Future research could extend this framework with a parallel P2P specification to test whether the EPU moderation effects identified here generalize to the credit intermediation channel of FinTech.

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Appendix A

Table 5.1: List of Countries by Region Used In Study

Region	Countries
Sub-Saharan Africa (22)	Angola, Benin, Botswana, Burkina Faso, Cameroon, Democratic Republic of the Congo, Gambia, Ghana, Kenya, Madagascar, Malawi, Mali, Mauritius, Namibia, Niger, Nigeria, Rwanda, Senegal, South Africa, Togo, Uganda, Zambia
Latin America & Caribbean (7)	Bolivia, Ecuador, El Salvador, Jamaica, Nicaragua, Paraguay, Uruguay
East Asia & Pacific (6)	Cambodia, Indonesia, Malaysia, Myanmar, Philippines, Thailand
South Asia (4)	Bangladesh, India, Nepal, Pakistan
Europe & Central Asia (3)	Albania, Hungary, Romania
Middle East & North Africa (3)	Jordan, Morocco, Qatar

Notes: Regional classification follows the World Bank country and lending groups classification (World Bank, 2025).