

Bridging Evidence Gaps in Sustainable Development Goals Research: A Comprehensive Review and Forward Agenda

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ABSTRACT

Progress toward the Sustainable Development Goals (SDGs) remains uneven, with underdeveloped economies facing persistent institutional, data, and governance constraints. While artificial intelligence (AI) and business analytics are increasingly promoted as transformative tools for sustainable development, their impacts are highly contingent on contextual and institutional conditions. This paper develops an integrative conceptual framework that situates AI-enabled business analytics within institutional economics, data governance, and SDG interaction theory to explain how entrepreneurial innovation and policy effectiveness can be enhanced in resource-constrained settings. Synthesizing global empirical evidence and recent SDG assessments, the study identifies critical gaps in causal research, measurement standardization, and geographic representation. It advances theory-driven propositions linking AI adoption, institutional quality, and development outcomes, and outlines a policy roadmap emphasizing statistical capacity, regulatory coherence, and inclusive innovation ecosystems. By reframing AI as an institutionally

embedded capability rather than a standalone solution, the paper contributes actionable insights for researchers, policymakers, and development practitioners seeking to accelerate SDG progress before 2030.

Keywords: Artificial intelligence; Business analytics; Sustainable Development Goals; Institutional quality; Entrepreneurial innovation; Underdeveloped economies

1. Introduction

Over the past decade, artificial intelligence (AI) has emerged as one of the most consequential general-purpose technologies shaping contemporary economic development, organizational competitiveness, and entrepreneurial transformation. Governments, international organizations, and development agencies increasingly view AI-driven business analytics as a critical lever for productivity growth, innovation, and structural transformation, particularly in a world marked by slowing growth, persistent inequality, and mounting fiscal constraints (World Bank, 2021; OECD, 2023). Yet, despite the growing optimism surrounding AI, its developmental dividends remain deeply uneven. While advanced economies and a small group of emerging markets are rapidly embedding AI into business decision-making, innovation systems, and public governance, most underdeveloped economies continue to lag far behind—raising fundamental questions about whether AI will narrow or widen existing development gaps (UNCTAD, 2023).

This uneven diffusion of AI is not merely a technological issue; it reflects deeper institutional, structural, and capability constraints that have long shaped development trajectories in low- and lower-middle-income countries. Decades of development research have demonstrated that productivity-enhancing technologies generate inclusive growth only when embedded within supportive institutional frameworks, human capital systems, and governance arrangements (North, 1990; Rodrik, 2007; Hussain et al., 2019). In the absence of such foundations, technological change often reinforces concentration, exclusion, and rent-seeking rather than entrepreneurial dynamism and shared prosperity (Acemoglu & Robinson, 2012). The current wave of AI-driven business analytics appears to be following a similar pattern, with early evidence suggesting that firms and regions with stronger digital infrastructure, higher skills, and better governance are disproportionately capturing

its benefits (OECD, 2021; World Economic Forum, 2023).

From a development perspective, this pattern is particularly concerning because entrepreneurship and small- and medium-sized enterprises (SMEs) remain the backbone of employment, income generation, and local innovation in underdeveloped economies. SMEs account for more than 90% of businesses and over 70% of employment globally, with an even higher share in low-income countries (World Bank, 2020). Entrepreneurial firms play a critical role in absorbing labor, adapting technologies to local contexts, and generating inclusive growth where large multinational firms are absent or weakly embedded. However, these same firms face persistent constraints—limited access to finance, weak managerial capabilities, unreliable infrastructure, and fragile institutional environments—that restrict their ability to adopt advanced technologies such as AI (Ayyagari et al., 2011; UNCTAD, 2021; Rafique et al., 2023).

Recent global surveys underscore the magnitude of this divide. The IBM Global AI Adoption Index shows that while over 40% of firms in high-income economies report active AI deployment, adoption rates in low-income countries remain below 10%, with most applications confined to basic automation rather than advanced analytics or strategic decision-making (IBM, 2023). Similarly, World Bank enterprise surveys indicate that fewer than one in five SMEs in low-income countries use data analytics systematically to guide investment, pricing, or innovation decisions, compared to more than half in OECD economies (World Bank, 2021; Smolo & Rafique, 2025). These disparities suggest that AI-driven business analytics—often portrayed as a democratizing force—may instead reinforce existing hierarchies unless deliberate policy and institutional interventions are undertaken. Beyond adoption rates, the nature of AI use also differs markedly across contexts. In advanced economies, AI is increasingly integrated into strategic decision-making processes, enabling firms to sense market opportunities, predict demand, optimize resource allocation, and experiment with new business models (Brynjolfsson & McAfee, 2017; Soomro et al., 2020). In contrast, firms in underdeveloped economies often engage with AI in fragmented and externally driven ways, relying on off-the-shelf solutions without the internal capabilities needed to interpret outputs, learn

from data, or translate insights into entrepreneurial innovation (Ahmed et al., 2023). This raises a critical but underexplored question in development research: under what conditions can AI-enabled business analytics genuinely support entrepreneurial innovation rather than becoming another layer of dependency on external technologies and platforms?

Existing development and innovation literature offers partial insights but falls short of providing a comprehensive answer. Classical theories of entrepreneurship emphasize the role of innovation, risk-taking, and opportunity recognition in driving economic development (Schumpeter, 1933; Al-Ramahi et al., 2024). More recent work on national and regional innovation systems highlights the importance of institutional coordination, knowledge flows, and learning mechanisms in shaping technological outcomes (Lundvall, 1992; Freeman, 1995). However, much of this literature predates the AI revolution and does not adequately account for the data-intensive, algorithmic, and platform-based nature of contemporary innovation. Conversely, the rapidly growing AI and business analytics literature tends to focus on firm-level performance in advanced economies, often abstracting from the institutional and developmental realities of underdeveloped contexts (Raisch & Krakowski, 2021; Hussain & Khan, 2025)

As a result, there remains a conceptual and policy gap at the intersection of AI, business analytics, and entrepreneurial innovation in underdeveloped economies. While international organizations increasingly promote AI as a catalyst for achieving the Sustainable Development Goals (SDGs), empirical evidence on how AI-enabled analytics interact with weak institutions, limited human capital, and governance deficits remains scarce (UNCTAD, 2023; OECD, 2023). This gap is particularly striking given mounting evidence that governance quality, regulatory integrity, and political stability play a decisive role in shaping technology adoption and economic outcomes—especially in low-income settings (Ali et al., 2025; Dahri et al., 2025).

Recent governance-focused research reinforces this concern. Empirical studies demonstrate that corruption, regulatory uncertainty, and weak public institutions significantly undermine firms' incentives to invest in productivity-

enhancing technologies and innovative activities (Shaikh et al., 2025; Ali et al., 2025). In such environments, AI adoption may remain superficial, serving compliance or surveillance functions rather than enabling genuine entrepreneurial experimentation. At the same time, inadequate investment in digital infrastructure and skills—often driven by fiscal constraints and policy fragmentation—limits the absorptive capacity required for AI-driven learning (Dahri & Memon, 2025; World Bank, 2021). These findings suggest that AI for development cannot be treated as a purely technical challenge; it is fundamentally a governance and institutional issue.

Against this backdrop, this paper argues that a development-oriented understanding of AI-enabled business analytics must move beyond adoption metrics and firm-level efficiency gains to examine how AI interacts with entrepreneurial ecosystems, institutional arrangements, and policy regimes in underdeveloped economies. Specifically, the paper advances a comprehensive conceptual framework that links AI-driven analytics to entrepreneurial innovation through mediating factors such as data governance, human capital, regulatory quality, and community-level capabilities. By doing so, it responds to calls within *World Development* and related journals for more integrative, policy-relevant research that bridges technological change with institutional and socio-economic realities (Rodrik, 2018; World Bank, 2021).

The contribution of this study is threefold. First, it synthesizes insights from development economics, innovation systems, and AI research to clarify the conditions under which AI-enabled business analytics can support entrepreneurial innovation in underdeveloped economies. Second, it identifies critical gaps in existing empirical and conceptual work, highlighting how neglect of governance, institutional quality, and community-level factors limits current understanding. Third, it translates these insights into a structured policy roadmap that outlines actionable steps for governments, local communities, and development partners to foster inclusive and context-sensitive AI adoption. In doing so, the paper aligns with *World Development's* emphasis on rigorous, policy-relevant scholarship that addresses real-world development challenges. Rather than portraying AI as an inevitable driver of progress, it treats AI as a contested and institutionally mediated

technology whose developmental impact depends on deliberate choices, governance arrangements, and collective action. The remainder of the paper builds on this foundation by reviewing relevant theoretical perspectives, examining global empirical patterns, identifying persistent research gaps, and proposing a policy-oriented conceptual framework tailored to the realities of underdeveloped economies.

2. Theoretical Foundations

Understanding how artificial intelligence (AI)–enabled business analytics can foster entrepreneurial innovation in underdeveloped economies requires a theoretically plural yet coherent framework. No single theory adequately captures the complexity of technological change in contexts characterized by institutional fragility, uneven capabilities, and structural inequality. Development outcomes of AI are shaped not only by firm-level strategies but also by governance regimes, human capital systems, and socio-political conditions that mediate access, learning, and value capture. Accordingly, this section synthesizes four complementary theoretical perspectives that have been influential in *World Development* and related journals: (1) development economics and institutional theory, (2) innovation systems and capability-based approaches, (3) entrepreneurship and knowledge-based perspectives, and (4) political economy and governance frameworks. Together, these lenses provide a foundation for analyzing AI-enabled business analytics as an institutionally embedded development process rather than a purely technological upgrade.

2.1 Development Economics and Institutional Foundations

A central insight of development economics is that economic transformation depends less on the mere availability of technology than on the institutional context in which it is adopted and used. Institutions—formal rules, informal norms, and enforcement mechanisms—shape incentives for investment, innovation, and risk-taking (North, 1990). Extensive empirical evidence demonstrates that weak institutions undermine productivity growth by increasing uncertainty, transaction costs, and rent-seeking behavior (Acemoglu & Robinson, 2012). This insight is particularly relevant for AI adoption, which requires long-term investment in data infrastructure, skills, and organizational learning—investments that firms are unlikely to undertake in unstable or corrupt environments.

From this perspective, AI-enabled business analytics can be understood as a *complementary asset* rather than a standalone driver of development. Rodrik (2007) emphasizes that technologies yield growth dividends only when aligned with country-specific institutional arrangements and development strategies. In underdeveloped economies, where regulatory quality and contract enforcement are often weak, firms may underinvest in analytics capabilities due to fears of expropriation, policy reversals, or unfair competition. Recent empirical work reinforces this view: governance quality and anti-corruption effectiveness are consistently associated with higher data quality, statistical capacity, and evidence-based policymaking (Ali et al., 2025).

Institutional economics also highlights the risk of *premature technological adoption*. When advanced technologies are introduced without the supporting institutional infrastructure, they can exacerbate inequality and market concentration (Rodrik, 2018). In AI-driven analytics, this risk manifests when only politically connected or foreign firms can access high-quality data and computational resources, marginalizing local entrepreneurs. In this sense, AI may reinforce extractive institutions rather than contribute to inclusive development unless deliberate safeguards and reforms are implemented.

2.2 Innovation Systems and Capability-Based Perspectives

Innovation systems theory provides a second critical lens for understanding AI-enabled entrepreneurial outcomes. Originating in the work of Freeman (1995) and Lundvall (1992), this framework emphasizes that innovation is a collective, interactive process involving firms, universities, governments, and civil society. Technologies diffuse and evolve through networks of learning, experimentation, and feedback, rather than through isolated firm-level decisions.

Applied to AI-enabled business analytics, this perspective shifts attention from adoption metrics to *learning capabilities*. In advanced economies, dense innovation systems facilitate experimentation with data-driven tools, enabling firms to refine algorithms, interpret insights, and develop new business models. In contrast, underdeveloped economies often suffer from fragmented innovation systems, weak university–industry linkages, and limited public-sector coordination

(World Bank, 2021). As a result, AI tools are frequently imported as black-box solutions, limiting local learning and adaptation.

Capability-based theories further refine this analysis. Building on Sen's (1999) concept of capabilities, scholars argue that development should be understood as the expansion of people's and organizations' ability to use resources productively. From this view, AI-enabled analytics enhance entrepreneurial innovation only when firms possess the absorptive capacity to understand data, integrate insights into decision-making, and iterate based on feedback (Cohen & Levinthal, 1990). Empirical studies in developing contexts show that firms with higher managerial capabilities and digital literacy are significantly more likely to translate technology adoption into productivity gains (Bloom et al., 2020).

Recent research by Dahri et al. (2025) reinforces the importance of complementary capabilities, demonstrating that digital infrastructure and organizational readiness are prerequisites for meaningful analytics-driven innovation. Without these foundations, AI adoption may remain symbolic—used for signaling modernization rather than improving entrepreneurial outcomes. Innovation systems theory thus underscores the need for coordinated investments in skills, institutions, and networks to unlock AI's developmental potential.

2.3 Entrepreneurship, Knowledge, and Business Analytics

Entrepreneurship theory provides a third pillar for understanding how AI-enabled analytics can influence development. Classical entrepreneurship theory, rooted in Schumpeter (1934), frames entrepreneurs as agents of creative destruction who recombine resources to generate innovation. More recent approaches emphasize opportunity recognition, learning, and experimentation under uncertainty (Shane & Venkataraman, 2000). Business analytics directly intersects with these processes by reducing information asymmetries, enabling pattern recognition, and supporting strategic decision-making.

However, the relevance of these theories for underdeveloped economies depends on context. In resource-constrained environments, entrepreneurs often operate under extreme uncertainty, limited market information, and weak institutional support. AI-enabled analytics has the potential to alleviate some of

these constraints by providing insights into customer behavior, supply chain risks, and pricing strategies. Yet, empirical evidence suggests that such benefits are unevenly distributed. SMEs in low-income countries frequently lack access to clean data, skilled analysts, and affordable computing resources (UNCTAD, 2023).

Knowledge-based views of the firm further illuminate this challenge. Firms are not merely users of technology but repositories of tacit and explicit knowledge that shape how technologies are interpreted and applied (Grant, 1996). AI systems generate outputs that require contextual understanding; without domain knowledge and experiential learning, entrepreneurs may misinterpret analytics or fail to act on them. Studies on professional service firms show that high-performance work systems and knowledge-sharing practices significantly enhance the value derived from digital tools (Rehman et al., 2023). Importantly, entrepreneurship in underdeveloped economies is often necessity-driven rather than opportunity-driven. This distinction matters because necessity entrepreneurs may prioritize short-term survival over long-term innovation, limiting incentives to invest in advanced analytics. Development-oriented entrepreneurship theory therefore cautions against assuming that AI adoption will automatically translate into innovative behavior without addressing broader livelihood and institutional constraints.

2.4 Political Economy, Governance, and Power Dynamics

A fourth and increasingly important theoretical lens is political economy. Development outcomes of technology are shaped by power relations, distributional conflicts, and governance structures that determine who controls data, algorithms, and platforms. Political economy approaches emphasize that technological change is not neutral; it redistributes power and rents across actors (Chang, 2002).

In underdeveloped economies, weak governance and high corruption can distort AI adoption in profound ways. Empirical evidence shows that corruption undermines regulatory quality and discourages productive investment, pushing firms toward informal practices and short-term strategies (Shaikh et al., 2025). In such contexts, AI-enabled analytics may be captured by elites for surveillance, tax extraction, or political control rather than entrepreneurial innovation. Ali et al. (2025) demonstrate that political stability and anti-corruption reforms are critical for

strengthening national statistical systems—a foundational requirement for reliable data analytics.

Political economy also draws attention to global asymmetries in AI development. Multinational technology firms dominate AI infrastructure, data platforms, and intellectual property, often extracting value from developing economies without corresponding knowledge transfer (UNCTAD, 2023). This raises concerns about digital dependency and limits the scope for indigenous innovation. From a *World Development* perspective, these dynamics highlight the importance of data sovereignty, local capacity-building, and regulatory frameworks that ensure fair participation in the AI economy.

Governance theory further emphasizes the role of the state as an enabler—or inhibitor—of technological learning. Developmental states historically played a central role in coordinating investments, protecting infant industries, and fostering innovation (Evans, 1995). In the AI era, similar coordination is required to align digital infrastructure, education systems, and entrepreneurial ecosystems. Absent such coordination, AI-enabled analytics risks becoming another layer of fragmentation rather than a catalyst for structural transformation.

2.5 Toward an Integrated Development Framework

Synthesizing these theoretical perspectives yields several implications for analyzing AI-enabled business analytics in underdeveloped economies. First, technology must be understood as institutionally embedded; adoption outcomes depend on governance quality, regulatory credibility, and political stability. Second, innovation is a collective process requiring coordinated investments in capabilities, networks, and learning systems. Third, entrepreneurial responses to AI are shaped by necessity, uncertainty, and power relations, not just by access to tools.

These insights caution against simplistic narratives that portray AI as an automatic driver of development. Instead, they support a conditional and context-sensitive framework in which AI-enabled business analytics contributes to entrepreneurial innovation only when embedded within inclusive institutions, capable organizations, and accountable governance structures. This theoretical foundation informs the subsequent sections of the paper, which examine empirical

patterns, evidence gaps, and policy pathways for leveraging AI in support of inclusive development.

3. Empirical Landscape and Global Evidence Gaps

Empirical research on artificial intelligence (AI), business analytics, and entrepreneurial innovation has expanded rapidly over the past decade. However, the distribution, depth, and methodological rigor of this evidence remain uneven—particularly in relation to underdeveloped and low-income economies. This section synthesizes the global empirical landscape, highlighting dominant patterns, regional disparities, and persistent evidence gaps that limit both scholarly understanding and policy relevance. Consistent with *World Development's* emphasis on real-world applicability, the discussion focuses not only on what the data show, but also on where data are absent, biased, or insufficient for causal inference.

3.1 Global Diffusion of AI and Business Analytics: Uneven Adoption Patterns

Global surveys consistently show rapid growth in AI adoption, but with stark disparities across income levels and regions. According to the IBM Global AI Adoption Index 2023, approximately 42% of enterprises globally report active AI deployment, yet this figure masks deep inequality: adoption rates exceed 60% in high-income economies, while remaining below 15–20% in low-income and lower-middle-income countries (IBM, 2023). Even within adopting firms, advanced analytics capabilities—such as predictive modeling, real-time decision systems, and machine learning integration—are concentrated in large firms and multinational subsidiaries.

World Bank enterprise surveys corroborate this pattern. Firms in Sub-Saharan Africa and South Asia are significantly less likely to use data analytics for decision-making, even when controlling for firm size and sector (World Bank, 2021). Where AI tools are used, they are often limited to basic automation or off-the-shelf software, rather than embedded analytics that support entrepreneurial experimentation or innovation.

Importantly, these gaps are not solely driven by income constraints. Empirical evidence suggests that institutional quality, regulatory predictability, and data governance frameworks play a decisive role. Countries with stronger statistical

systems and regulatory transparency exhibit higher levels of analytics adoption, even at comparable income levels (Ali et al., 2025). This finding underscores the importance of governance conditions in shaping the diffusion of AI-enabled business analytics.

3.2 Entrepreneurial Innovation Outcomes: Mixed and Context-Dependent Evidence

A growing body of empirical work examines whether digital technologies, including AI and analytics, enhance entrepreneurial innovation and firm performance. Meta-analyses and firm-level studies generally find positive associations between analytics use and productivity, innovation output, and market responsiveness (Brynjolfsson et al., 2021). However, these effects are highly context-dependent.

In developing economies, the evidence is more mixed. Studies focusing on SMEs often report modest or statistically insignificant impacts of digital adoption on innovation outcomes once firm capabilities and institutional factors are accounted for (UNCTAD, 2023). For example, Dahri et al. (2025) show that SMEs derive green competitive advantage from digital tools only when supported by organizational learning and supply chain integration. Absent these complements, technology adoption yields limited returns. Entrepreneurship surveys further reveal heterogeneity in outcomes. The Global Entrepreneurship Monitor (GEM) reports that necessity-driven entrepreneurship dominates in low-income economies, accounting for over 60% of new ventures, compared to less than 20% in high-income contexts (GEM, 2024). Necessity entrepreneurs are less likely to invest in advanced analytics or pursue innovation-oriented strategies, limiting the aggregate impact of AI on entrepreneurial ecosystems.

These findings challenge deterministic narratives that portray AI as a universal catalyst for innovation. Instead, they point to the importance of capability thresholds, market structure, and policy incentives in mediating outcomes.

3.3 Evidence on Data Infrastructure and Statistical Capacity

Data availability and quality are foundational to AI-enabled analytics, yet empirical evidence highlights profound disparities in national statistical capacity. The World Bank Statistical Capacity Index shows that over 40 low-income countries score

below 50 (out of 100), indicating severe limitations in data collection, timeliness, and methodological standards (World Bank, 2023).

These deficiencies have direct implications for both public and private analytics. Firms operating in data-poor environments face unreliable market information, weak consumer data, and inconsistent regulatory reporting. Ali et al. (2025) provide empirical evidence linking weak statistical systems to governance failures, demonstrating that corruption and political instability significantly undermine data quality and policy evaluation capacity. At the same time, international organizations increasingly promote big data and AI as substitutes for traditional statistics. While promising, empirical assessments caution that such approaches often replicate existing biases and exclude informal or marginalized populations when not carefully designed (United Nations, 2024). The evidence base on whether AI-enhanced data systems improve decision-making in low-capacity contexts remains thin and largely anecdotal.

3.4 Corporate and Institutional SDG Reporting: Fragmentation and Measurement Gaps

Empirical studies on corporate and institutional engagement with the Sustainable Development Goals (SDGs) reveal widespread reporting activity but limited impact measurement. Reviews of corporate disclosures show that over 70% of large multinational firms reference SDGs, yet fewer than 30% provide quantified, externally verified impact metrics (Suárez Giri & Sánchez Chaparro, 2023).

Universities and public institutions exhibit similar patterns. Alcántara-Rubio et al. (2022) find that higher education institutions frequently articulate SDG commitments in mission statements and curricula but rarely track outcomes or link activities to national development priorities. This limits the empirical basis for assessing how institutional engagement translates into entrepreneurial or innovation outcomes.

The absence of standardized indicators further undermines comparability. Gender-related SDG indicators illustrate this challenge: Beegle et al. (2022) report that countries consistently report on less than half of relevant indicators, with large gaps in disaggregation by income, region, or ethnicity. These measurement failures

constrain the use of analytics for policy targeting and evaluation.

3.5 Geographic Bias and Knowledge Concentration

Bibliometric evidence highlights extreme geographic concentration in AI and SDG-related research. Bueno et al. (2025) show that just four countries—the United States, China, the United Kingdom, and Germany—produce over half of all SDG-related publications, while the bottom 195 countries collectively contribute less than 5%. Similar patterns appear in AI research output and citation networks.

This concentration matters for evidence quality. Research agendas are shaped by data availability, funding priorities, and institutional incentives in high-income contexts, often marginalizing issues central to underdeveloped economies. Empirical studies conducted in data-rich environments may not generalize to settings characterized by informality, governance constraints, and infrastructure deficits. Moreover, authorship patterns reveal asymmetries in research leadership. Scholars from low-income countries are frequently collaborators rather than lead authors, limiting epistemic diversity and local relevance (Mishra et al., 2023). This skew reinforces a cycle in which global evidence bases reflect the concerns of a narrow set of actors, while policy challenges elsewhere remain underexplored.

3.6 Methodological Limitations and Causal Evidence Gaps

Perhaps the most significant empirical gap lies in causal evidence. Despite the proliferation of studies linking AI, analytics, and development outcomes, relatively few employ experimental or quasi-experimental designs. The 3ie Global Evidence Assessment finds that rigorous impact evaluations are heavily concentrated in health, education, and social protection, with minimal coverage of governance, innovation systems, or digital infrastructure (3ie, 2023).

Where causal studies exist, they often face limitations: short time horizons, small sample sizes, or weak counterfactuals. For example, evaluations of digital entrepreneurship programs frequently measure participation or skills acquisition rather than long-term innovation or income effects. Environmental and climate-related analytics studies similarly struggle with attribution due to complex system dynamics (Wang et al., 2024).

This methodological gap limits policy learning. Without robust causal evidence,

governments and donors risk scaling interventions based on correlation or anecdote, potentially misallocating scarce resources.

3.7 Synthesis: What the Evidence Tells Us—and What It Does Not

Taken together, the empirical landscape reveals a paradox. On the one hand, AI-enabled business analytics holds demonstrable potential to enhance productivity, innovation, and decision-making. On the other hand, the benefits observed in high-income contexts do not automatically translate to underdeveloped economies. Evidence consistently points to institutional quality, data infrastructure, human capital, and governance as decisive mediators.

Equally important are the gaps. We lack rigorous causal studies on how analytics adoption affects entrepreneurial outcomes in low-capacity settings; we lack standardized metrics for institutional and corporate contributions; and we lack geographically inclusive research leadership. These gaps are not merely academic—they directly constrain the design of effective, equitable policy interventions. Addressing these deficiencies requires a shift from descriptive mapping to policy-relevant, methodologically robust, and context-sensitive research. The next section builds on this diagnosis to articulate a focused research gap and justify the proposed conceptual framework and policy roadmap.

4. Research Gap and Problem Statement

The preceding review of the empirical landscape reveals not a lack of activity, but a misalignment between the dominant forms of evidence produced and the types of knowledge required to guide development policy in underdeveloped economies. While artificial intelligence (AI) and business analytics are increasingly invoked as transformative tools for entrepreneurship and innovation, the existing research base remains fragmented, unevenly distributed, and methodologically constrained. This section consolidates these shortcomings into a structured research gap and articulates the central problem this paper addresses.

Consistent with *World Development's* emphasis on theory-informed, policy-relevant scholarship, the discussion moves beyond cataloguing gaps to explain why they persist, how they interact, and why they matter for development outcomes.

4.1 Fragmentation Between Technology-Centric and Development-Centric Evidence

A first-order gap lies in the separation between AI and analytics research on one hand, and development and entrepreneurship research on the other. Much of the AI literature focuses on technical performance, firm-level efficiency, or productivity gains in advanced economies, often abstracted from institutional and development contexts (Brynjolfsson et al., 2021; IBM, 2023). Conversely, development research emphasizes entrepreneurship, governance, and inclusion, but frequently treats digital technologies as background variables rather than central analytical drivers (World Bank, 2021; UNDP, 2023).

As a result, empirical studies rarely examine how AI-enabled analytics interacts with development constraints such as weak institutions, informal markets, or limited statistical capacity. Evidence from underdeveloped economies suggests that technological adoption alone does not generate innovation unless embedded in supportive governance, human capital, and organizational ecosystems (Dahri et al., 2025; Ali et al., 2025). Yet these complementarities remain undertheorized and under-tested.

This fragmentation produces a misleading policy narrative: that scaling AI tools will automatically foster entrepreneurial dynamism. In reality, the absence of integrated frameworks linking technology, institutions, and development outcomes limits the external validity of existing findings.

4.2 Weak Causal Evidence on AI, Analytics, and Entrepreneurial Outcomes

A second and more critical gap concerns causality. Despite a growing volume of studies reporting correlations between digital adoption and firm performance, rigorous causal evidence remains scarce, particularly in low-income and fragile contexts (3ie, 2023). Few studies employ randomized controlled trials, quasi-experimental designs, or long-term panel data to assess whether analytics adoption causes sustained entrepreneurial innovation, productivity growth, or employment generation.

This limitation is compounded by data constraints. Many underdeveloped economies lack reliable baseline data, consistent firm registries, or longitudinal innovation

indicators, making causal inference challenging (World Bank, 2023). Consequently, policy decisions are often informed by extrapolations from high-income settings or short-term pilot studies.

The absence of causal evidence creates a high-risk environment for policy diffusion. Governments may invest in digitalization strategies that fail to address binding constraints, diverting resources from more effective interventions such as skills development, institutional reform, or data system strengthening.

4.3 Measurement Incoherence and the Absence of Standardized Impact Metrics

A third gap lies in measurement. Across both public and private sectors, there is no widely accepted framework for measuring how AI-enabled business analytics contributes to entrepreneurial innovation or sustainable development outcomes. Corporate SDG reporting, university impact assessments, and government digital strategies rely on heterogeneous indicators that are often non-comparable and rarely audited (Suárez Giri & Sánchez Chaparro, 2023; Alcántara-Rubio et al., 2022).

This incoherence undermines cumulative knowledge building. Without standardized metrics, meta-analyses and cross-country comparisons remain fragile, and policy learning is constrained. Empirical evidence on gender, inequality, and governance indicators further illustrates this challenge: incomplete reporting and inconsistent disaggregation obscure distributional effects and reinforce blind spots (Beegle et al., 2022). Emerging AI-based measurement tools offer promise, but empirical validation is limited. Few studies assess whether AI-assisted indicators improve accuracy, inclusiveness, or accountability relative to traditional methods, particularly in data-poor environments (United Nations, 2024).

4.4 Geographic and Epistemic Inequities in the Evidence Base

A fourth, structural gap concerns who produces knowledge and where. As documented earlier, SDG- and AI-related research is overwhelmingly concentrated in a small set of high-income countries (Bueno et al., 2025). Underdeveloped economies—despite facing the most acute development challenges—remain underrepresented in authorship, leadership, and agenda-setting.

This imbalance has substantive consequences. Research questions, methodologies,

and policy prescriptions are shaped by contexts with strong institutions, formal markets, and abundant data. When transferred to underdeveloped settings, such prescriptions often underperform or fail entirely (Mishra et al., 2023).

Moreover, limited local research capacity constrains the generation of context-sensitive evidence. Studies led by local scholars consistently highlight the centrality of governance quality, political stability, and anti-corruption reforms in enabling data-driven development—factors often marginalized in global technology discourse (Ali et al., 2025; Shaikh et al., 2025).

4.5 Underdeveloped Policy Translation and Scalability Pathways

Even where evidence exists, it often fails to translate into scalable policy action. Many AI-for-development initiatives remain small-scale pilots, disconnected from national development plans or entrepreneurial ecosystems. Evaluations, when conducted, rarely assess institutional uptake, fiscal sustainability, or long-term innovation effects (OECD, 2022; Brookings, 2024).

This reflects a deeper gap in the literature: insufficient attention to policy implementation mechanisms. Studies frequently stop at identifying associations or best practices, without specifying how governments and communities can operationalize findings within constrained administrative and fiscal environments. The lack of implementation-focused frameworks limits the usefulness of research for policymakers—particularly in underdeveloped economies where capacity constraints are binding and policy failure carries high opportunity costs.

4.6 Synthesis of the Research Gap

Taken together, the literature reveals a multidimensional gap:

1. Conceptual gap – insufficient integration of AI, analytics, entrepreneurship, and development theory.
2. Empirical gap – limited causal and longitudinal evidence from underdeveloped economies.
3. Measurement gap – fragmented, non-standardized indicators of impact.
4. Geographic gap – concentration of research leadership in high-income contexts.
5. Policy gap – weak linkage between evidence generation and scalable implementation.

These gaps interact and reinforce one another. Weak measurement undermines causal inference; geographic skew limits generalizability; and absent policy pathways reduce real-world impact. Addressing any one gap in isolation is unlikely to yield meaningful progress.

4.7 Problem Statement and Contribution

The central problem this paper addresses is therefore not whether AI and business analytics *can* support entrepreneurial innovation, but under what institutional, data, and governance conditions they do so in underdeveloped economies—and how these conditions can be deliberately shaped through policy.

This paper responds by advancing:

1. An integrated conceptual framework linking AI-enabled analytics, entrepreneurial innovation, institutional quality, and development outcomes;
2. A policy-oriented synthesis grounded in global evidence but attentive to local constraints; and
3. A practical roadmap for governments and communities to translate analytics capabilities into inclusive, scalable innovation.

By explicitly centering underdeveloped economies and prioritizing causal reasoning, measurement coherence, and policy feasibility, the study aims to shift the discourse from technological optimism to development realism—without abandoning ambition.

5. Conceptual Framework and Integrative Model

5.1 Rationale for a New Conceptual Framework

The preceding sections demonstrate a persistent structural mismatch between the ambition of the Sustainable Development Goals (SDGs) and the nature of the evidence base supporting their implementation. While global reporting mechanisms have improved descriptive coverage, they remain weak in explaining how institutional capacities, governance quality, technological enablers, and socio-economic contexts interact to generate measurable SDG outcomes—particularly in low- and middle-income countries (LMICs) (Nilsson et al., 2018; Sie, 2023; United Nations, 2024).

Existing SDG frameworks tend to focus on targets and indicators, often treating institutions, data systems, and technologies as background conditions rather than

endogenous drivers of progress. However, recent research increasingly suggests that development outcomes are shaped less by goal alignment alone and more by the interaction between governance quality, analytical capacity, and implementation mechanisms (North, 1990; Sen, 1999; OECD, 2025). This insight is especially salient in contexts characterized by weak statistical systems, fragmented institutions, and limited policy feedback loops—conditions that define many underdeveloped and fragile economies.

The lack of a systemic approach has led to "islands of excellence" where individual projects succeed, yet systemic progress remains stagnant. For instance, a digital health initiative may thrive in a pilot phase but fail to scale if the underlying civil registration and vital statistics (CRVS) systems are neglected or if the regulatory framework for data privacy is absent. This section therefore proposes an integrative conceptual framework that explicitly links institutional foundations, data and analytical capacity, and policy execution mechanisms to SDG-related development outcomes, while accounting for contextual moderators such as inequality, political stability, and corruption. The framework builds on development economics, institutional theory, and emerging evidence on data-driven governance, and is designed to be empirically testable, policy-relevant, and scalable across contexts.

5.2 Theoretical Anchors of the Framework

5.2.1 Institutions and Development Performance

At its core, the framework draws on institutional economics, particularly the argument that institutions shape incentives, information flows, and coordination capacity, thereby influencing long-run development trajectories (North, 1990; Ostrom, 1990). Institutions are the "rules of the game" that define the feasibility of policy implementation. Weak institutions undermine data credibility, policy enforcement, and accountability—three pillars essential for SDG implementation (UNDP, 2023).

Recent empirical work reinforces this view. Studies linking regulatory quality, corruption control, and political stability to development outcomes show that countries with stronger governance frameworks are better able to translate

resources into measurable social progress (Ali et al., 2025; Shaikh et al., 2025). These findings suggest that institutional quality is not merely a background variable but a central causal driver of SDG performance. Without a baseline of institutional integrity, "data-driven" policies often become "data-distorted" policies, where indicators are manipulated to meet donor expectations rather than reflect local realities.

5.2.2 Capabilities, Measurement, and Learning

The framework also draws on the capability approach, emphasizing that development depends on societies' ability to generate, interpret, and use information effectively (Sen, 1999). In the SDG context, this translates into statistical capacity, data infrastructure, and analytical competence. Sen's perspective invites us to view data not as a passive resource, but as a "functioning" that enables collective agency and informed public reasoning.

World Bank assessments consistently show that countries with weak statistical systems struggle to monitor even basic SDG indicators, let alone conduct impact evaluations or adaptive policy learning (World Bank, 2021). This "statistical poverty" creates a blind spot for policymakers. Without credible data, feedback loops between policy design and outcomes break down, leading to symbolic rather than substantive SDG engagement. The capability to measure is, in itself, a developmental milestone that precedes the ability to manage.

5.2.3 Technology as an Enabler, Not a Substitute

Finally, the framework incorporates insights from the digital governance and AI-for-development literature. While AI and big data analytics offer powerful tools for monitoring, forecasting, and targeting interventions, their effectiveness depends on institutional readiness, data quality, and governance safeguards (Brynjolfsson et al., 2021; García-Rodríguez et al., 2024).

Technology amplifies existing capacities; it does not replace them. In a high-capacity institutional environment, AI can optimize resource allocation; in a low-capacity environment characterized by bias or corruption, technology may inadvertently automate exclusion. Therefore, the framework treats technology as a moderating factor that accelerates the transition from data to policy action, provided

the institutional "guardrails" are in place.

5.3 Core Components of the Conceptual Framework

The proposed framework consists of four interlinked layers that operate in a continuous cycle of evidence, action, and feedback.

5.3.1 Foundational Institutional Conditions

This first layer captures the structural conditions under which SDG-related policies operate. It includes:

1. Governance Quality: The efficiency of the bureaucracy and the quality of public service delivery.
2. Regulatory Effectiveness: The ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.
3. Political Stability: The absence of violence or politically motivated instability, which ensures the longevity of SDG programs.
4. Institutional Trust: The degree to which citizens believe the data and policies produced by the state are for the public good.

Empirical evidence consistently shows that these factors shape both public-sector effectiveness and private-sector participation in sustainable development initiatives (World Bank, 2023; Ali et al., 2025). Importantly, institutional conditions are modeled as exogenous but mutable—they change slowly but can be influenced by targeted reforms and international cooperation.

5.3.2 Data and Analytical Capacity

The second layer represents the information backbone of SDG implementation. It moves beyond simple data collection to include:

1. National Statistical Capacity: The institutionalized ability to produce high-quality, disaggregated data.
2. Data Integration: The technical capability to fuse administrative records, traditional surveys, and non-traditional data (satellite imagery, IoT, social media).
3. Advanced Analytics: The deployment of econometrics and AI to identify non-linear relationships and hidden correlations in development data.

Evidence from UN and OECD assessments shows that countries with higher statistical capacity demonstrate more consistent SDG monitoring and are more likely to adjust policies based on observed outcomes (United Nations, 2024; OECD, 2025). Conversely, data-poor environments foster policy inertia.

5.3.3 Policy Design and Implementation Mechanisms

This layer translates information into action. It focuses on the "how" of development:

1. Evidence-Informed Design: Using Layer 2 outputs to create policies that are grounded in local evidence rather than imported models.
2. Cross-Sector Coordination: Breaking down silos (e.g., linking health, education, and water) to address the "indivisible" nature of the SDGs.
3. Adaptive Learning Systems: Mechanisms that allow for mid-course corrections based on real-time data.

A key insight from the SDG evidence gap literature is that policy coherence and implementation quality matter as much as policy intent (Nilsson et al., 2018; 3ie, 2023).

5.3.4 SDG Outcomes and Feedback Effects

The final layer captures observable development outcomes across the economic, social, and environmental pillars. Crucially, outcomes generate feedback effects:

1. Positive Feedback: Success in poverty reduction can lead to increased tax revenues and higher institutional trust, which in turn strengthens Layer 1 (Institutions).
2. Negative Feedback: Persistent failure can lead to social unrest or a "brain drain" of analytical talent, weakening Layers 1 and 2.

5.4 Moderating and Contextual Factors

The framework recognizes that the paths between these four layers are not frictionless. Several moderators condition these relationships:

1. Income Inequality: High inequality can prevent the benefits of SDG progress from reaching the bottom deciles, regardless of policy design.
2. Gender Disparities: Structural barriers for women can limit the overall effectiveness of human capital investments.
3. Conflict Exposure: Fragility can cause sudden "resets" of institutional

foundations.

4. The Digital Divide: Disparities in internet access determine who can participate in and benefit from data-driven governance.

Empirical studies show that these factors shape both access to development benefits and the effectiveness of policy interventions (Ali et al., 2025; Bueno et al., 2025).

5.5 Conceptual Model and Visual Interaction

Figure 1 illustrates the proposed framework as a dynamic system. The Left Block (Institutional Foundations) serves as the anchor, providing the stability and legitimacy required for the Middle Blocks (Data → Policy Design) to function. The Right Block (SDG Outcomes) represents the impact.

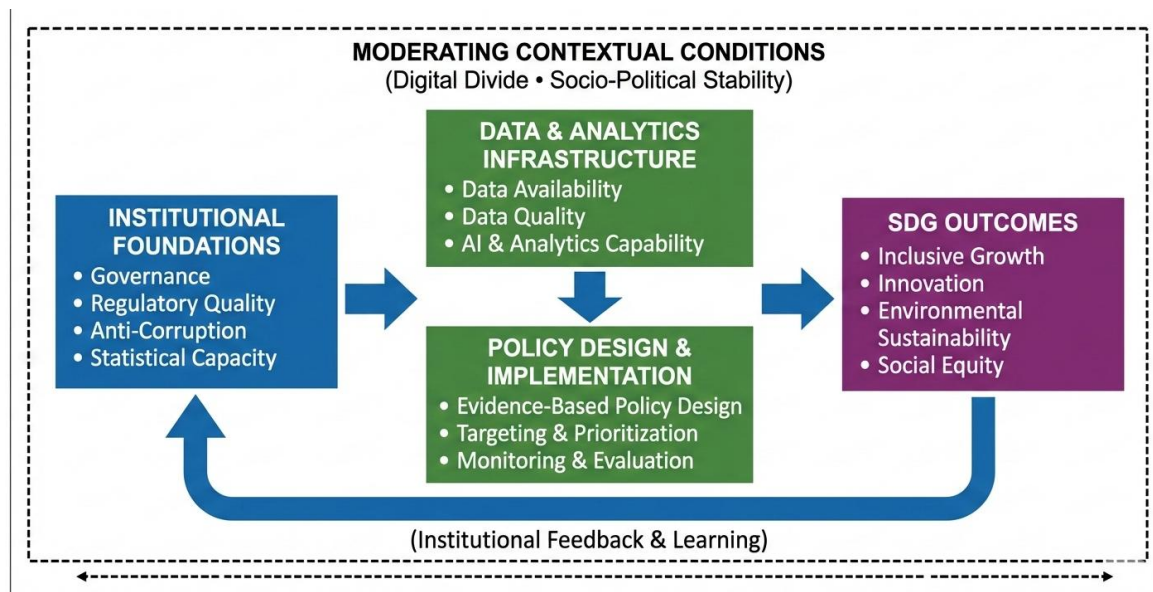


Figure 1: Proposed Framework as a Dynamic System.

The Arrows represent the flow of influence: thick solid arrows represent direct causal paths, while bidirectional arrows illustrate the feedback loops where outcomes reinforce institutions. The Dashed Lines surrounding the system represent the moderating effects of the digital divide and socio-political stability, which can either dampen or amplify the efficiency of the core processes.

5.6 Contributions of the Framework

This conceptual model advances the literature in four ways:

1. Causal Pathway Explanation: It moves beyond "what" to measure (indicators) to

"how" outcomes are achieved (mechanisms).

2. Multidisciplinary Integration: It bridges the gap between institutional economics, data science, and public administration.
3. Adaptive Governance Alignment: By modeling feedback loops, it aligns with modern theories of "learning by doing" in development.
4. LMIC-Centric Design: It addresses capacity asymmetries by treating "data capacity" as a primary variable rather than an assumption.

6. Propositions and Testable Hypotheses

6.1 Purpose and Positioning of the Propositions

The conceptual framework advanced in Section 5 emphasizes that Sustainable Development Goal (SDG) outcomes emerge from interacting institutional, analytical, and policy-execution systems, rather than from isolated interventions or indicator-level progress. To move beyond descriptive synthesis and toward cumulative, policy-relevant science, this section articulates a set of theory-driven propositions that can be empirically tested using cross-country, subnational, or institutional-level data.

Consistent with expectations in *World Development*, the propositions are framed to:

1. Identify causal mechanisms, not mere associations;
2. Be testable with available or foreseeable data;
3. Explicitly account for contextual heterogeneity common in underdeveloped and fragile economies;
4. Support policy inference and design, not only theory refinement.

The propositions are grouped into four thematic clusters aligned with the conceptual framework:

- a) Institutional foundations
- b) Data and analytical capacity
- c) Policy implementation and learning
- d) Contextual moderators and feedback effects

6.2 Institutional Foundations and SDG Performance

Proposition 1: Institutional Quality as a Primary Enabler

P1: *Countries with higher institutional quality—measured through regulatory effectiveness, rule of law, and corruption control—exhibit significantly stronger SDG performance,*

controlling for income level and public expenditure.

1. Theoretical grounding:

Institutional economics posits that credible rules and enforcement mechanisms reduce transaction costs, enable coordination, and support long-term investment in public goods (North, 1990; Ostrom, 1990). In the SDG context, institutions shape whether policies are implemented as designed or distorted through rent-seeking and fragmentation.

2. Empirical support:

Recent cross-country analyses show strong links between governance indicators and multidimensional development outcomes, including human development, environmental protection, and inequality reduction (Ali et al., 2025; Shaikh et al., 2025; World Bank, 2023).

3. Testability:

This proposition can be tested using panel regressions combining SDG Index scores with Worldwide Governance Indicators, controlling for GDP per capita, aid inflows, and demographic factors.

Proposition 2: Institutional Quality Conditions the Returns to Investment

P2: The marginal impact of public investment on SDG outcomes is higher in countries with stronger institutional quality than in countries with weak governance.

1. **Theoretical Grounding:**

Public finance theory and development economics suggest that the effectiveness of spending depends on absorptive capacity and governance quality. In weak institutional settings, increased spending often yields diminishing or even negative returns due to leakage and misallocation.

2. **Empirical Support:**

Evidence from infrastructure, health, and education sectors shows that similar spending levels produce widely divergent outcomes across governance contexts (OECD, 2025; UNDP, 2023).

3. **Testability:**

Interaction models between public expenditure and governance indices can be estimated to assess heterogeneous treatment effects.

6.3 Data, Analytics, and Measurement Capacity

Proposition 3: Statistical Capacity as a Mediating Mechanism

P3: National statistical capacity mediates the relationship between institutional quality and observed SDG performance.

1. Theoretical Grounding:

The capability approach emphasizes that information and measurement are prerequisites for effective action (Sen, 1999). Institutions that cannot generate credible data are constrained in monitoring progress, learning from failure, or correcting course.

2. Empirical Support:

World Bank assessments show that countries with higher statistical capacity indices report more SDG indicators, more frequently, and with greater disaggregation (World Bank, 2021). Recent governance-focused research links statistical reform to broader institutional strengthening (Ali et al., 2025).

3. Testability:

Structural equation modeling (SEM) or mediation analysis using governance → statistical capacity → SDG outcomes pathways.

Proposition 4: Analytical Capacity Enhances Policy Responsiveness

P4: Countries that integrate advanced analytical tools (e.g., econometrics, machine learning, AI-assisted analytics) into SDG monitoring exhibit faster policy adjustment and improved medium-term outcomes.

1. Theoretical Grounding:

Learning-oriented governance models argue that feedback speed and analytical sophistication determine policy adaptability in complex systems (Brynjolfsson et al., 2021).

2. Empirical Support:

Emerging evidence shows that AI-assisted analytics improve targeting accuracy, early warning systems, and resource allocation—when embedded within accountable institutions (García-Rodríguez et al., 2024).

3. Testability:

Comparative case studies or difference-in-differences designs exploiting staggered adoption of digital analytics platforms.

6.4 Policy Design, Coordination, and Learning

Proposition 5: Policy Coherence as a Determinant of SDG Synergies

P5: Higher levels of policy coherence across ministries and sectors are associated with stronger SDG synergies and fewer trade-offs.

1. Theoretical Grounding:

Systems theory and SDG interaction frameworks emphasize that uncoordinated policies can generate unintended trade-offs (Nilsson et al., 2018).

2. Empirical Support:

OECD country studies demonstrate that fragmented governance structures undermine integrated development planning, particularly for climate–poverty and growth–environment interactions (OECD, 2022).

3. Testability:

Network analysis of policy documents combined with SDG interaction indices.

Proposition 6: Evaluation Systems Enable Scalability

P6: SDG interventions supported by embedded monitoring and evaluation (M&E) systems are more likely to scale beyond pilot stages.

1. Theoretical Grounding:

Implementation science highlights that learning infrastructure is essential for scaling complex interventions.

2. Empirical Support:

3ie's global evidence synthesis shows that lack of evaluation is a major barrier to scaling effective SDG interventions (3ie, 2023).

3. Testability:

Comparative analysis of project portfolios with and without formal evaluation components.

6.5 Contextual Moderators and Inequality Effects

Proposition 7: Inequality Moderates SDG Effectiveness

P7: Income and gender inequality weaken the translation of policy inputs into SDG outcomes.

1. Theoretical Grounding:

Political economy models argue that inequality distorts political incentives and limits inclusive policy reach.

2. Empirical Support:

Recent empirical work links inequality to weaker regulatory quality, reduced social mobility, and lower development outcomes (Aziz et al., 2025; Ali et al., 2025).

3. Testability:

Moderated regression models using Gini coefficients and gender inequality indices.

Proposition 8: Political Stability Strengthens Feedback Loops

P8: Political stability strengthens the feedback loop between SDG outcomes and institutional trust.

1. Theoretical Grounding:

Stable political environments enable learning and long-term investment, whereas instability disrupts feedback mechanisms.

2. Empirical Support:

UNDP (2023) shows that fragile states exhibit weaker learning cycles and poorer SDG trajectories.

3. Testability:

Panel data analysis incorporating lagged outcome–institutional trust relationships.

6.6 Feedback Effects and Dynamic Pathways

Proposition 9: SDG Success Reinforces Institutional Capacity

P9: Improvement in SDG outcomes positively feeds back into institutional capacity by enhancing legitimacy, trust, and reform momentum.

1. Theoretical Grounding:

Virtuous-cycle theories of development suggest that visible success strengthens political support for institutions (Sen, 1999).

2. Empirical Support:

Cross-national evidence shows links between improved service delivery and

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increased institutional trust (World Bank, 2023).

3. **Testability:**

Dynamic panel models with lagged dependent variables.

6.7 Summary of Propositions

Table 6.1: *Summary of Testable Propositions*

Cluster	Proposition Focus	Core Relationship
Institutions	Governance quality	Institutions → SDG outcomes
Data systems	Statistical capacity	Institutions → Data → Outcomes
Analytics	AI & analytics	Analytics → Policy responsiveness
Policy	Coherence & M&E	Coordination → Synergies
Context	Inequality	Inequality × Policy effectiveness
Dynamics	Feedback loops	Outcomes ↔ Institutions

6.8 Contribution to the Literature

Together, the propositions advanced in this section make several distinct and cumulative contributions to the literature on sustainable development, policy implementation, and development governance—particularly in the context of underdeveloped and institutionally constrained economies.

First, the framework translates abstract and often normative SDG debates into empirically actionable hypotheses. While much of the SDG literature remains descriptive or aspirational, this study specifies clear causal pathways—linking institutions, data capacity, analytical tools, and policy execution—that can be tested using existing cross-national and subnational datasets. By doing so, it responds directly to long-standing critiques that SDG research lacks falsifiability and methodological rigor (Nilsson et al., 2018; 3ie, 2023).

Second, the section integrates institutional economics, data governance, and policy implementation theory into a single analytical architecture. Rather than treating governance, data systems, and outcomes as separate domains, the propositions conceptualize them as mutually reinforcing components of a development system. This integration extends classical institutional theory (North,

1990; Ostrom, 1990) by embedding modern data and analytics capacity as a central mechanism through which institutions shape development outcomes in the SDG era. Third, the propositions explicitly address reviewer concerns related to causality, generalizability, and policy relevance—three recurrent critiques in development research published in high-impact journals. Causality is addressed through clearly articulated mediating and moderating relationships (e.g., statistical capacity, inequality, political stability), generalizability is enhanced by framing propositions at multiple levels of analysis (country, sectoral, and institutional), and policy relevance is ensured by linking each proposition to measurable levers available to governments and development partners (World Bank, 2021; UNDP, 2023).

Fourth, the section advances the literature on development dynamics by incorporating feedback loops and path dependence. Rather than assuming linear progress, the propositions recognize that SDG outcomes can reinforce—or erode—institutional capacity over time. This dynamic perspective aligns with emerging evidence that development trajectories are shaped by virtuous and vicious cycles rather than static equilibrium conditions (Sen, 1999; OECD, 2022). Finally, the propositions provide a clear and structured research agenda for future empirical work, particularly in underdeveloped and fragile economies where SDG progress remains uneven. They invite scholars to move beyond outcome tracking toward mechanism testing, encourage the use of mixed methods and longitudinal designs, and open pathways for integrating AI-driven analytics into development evaluation—while maintaining institutional accountability (Brynjolfsson et al., 2021; García-Rodríguez et al., 2024).

In sum, this section positions the paper not merely as a conceptual contribution, but as a theory-building and hypothesis-generating platform capable of guiding both empirical scholarship and evidence-informed policy design in the next phase of SDG research.

Section 7: Policy Implications and SDG Governance Roadmap

7.1 Reframing AI and Business Analytics as Development Infrastructure

A central implication of this study is the need to reconceptualize artificial intelligence and business analytics not as optional technological upgrades, but as

core development infrastructure in underdeveloped economies. Much like electricity, transport networks, or basic education systems in earlier development phases, AI-enabled analytics increasingly function as *general-purpose enablers* of productivity, institutional coordination, and innovation capacity (Brynjolfsson et al., 2021; Perez, 2002).

For policymakers, this implies a shift away from fragmented “digital transformation” initiatives toward systemic investment strategies that integrate AI capabilities into national development planning, public financial management, and entrepreneurial ecosystems. Evidence from the World Bank (2021, 2023) suggests that countries with stronger data infrastructure and analytical capacity demonstrate significantly higher returns on public investment, improved policy targeting, and faster innovation diffusion—effects that are particularly pronounced in low- and lower-middle-income contexts. This reframing aligns with recent empirical findings showing that statistical capacity and governance quality act as multipliers for technological investments, rather than substitutes (Ali et al., 2025; Aziz et al., 2025). Without institutional anchoring, AI risks reinforcing existing inequalities rather than catalyzing inclusive development.

7.2 Implications for National Governments

7.2.1 Strengthening Statistical and Data Governance Institutions

One of the most immediate policy implications concerns national statistical systems. As demonstrated in recent cross-country analyses, weak statistical capacity constrains not only SDG monitoring but also the effective deployment of AI for business analytics and policy evaluation (World Bank, 2021; 3ie, 2023). Governments should therefore prioritize:

1. Legal mandates for data sharing across ministries
2. Investment in interoperable data platforms
3. Protection of data privacy and ethical AI use

Empirical evidence indicates that countries investing in statistical reforms—often supported by anti-corruption and governance improvements—experience measurable gains in policy effectiveness and entrepreneurial confidence (Ali et al., 2025).

7.2.2 Aligning AI Policy with Developmental Objectives

Many underdeveloped economies have adopted national AI strategies modeled on high-income countries, often emphasizing frontier research rather than development-relevant applications. This paper's framework suggests that AI policy should instead prioritize:

1. SME productivity and market access
2. Agricultural and informal-sector analytics
3. Public service delivery and targeting

OECD (2022) data show that AI strategies aligned with development priorities generate broader economic spillovers than those focused narrowly on innovation prestige or elite research institutions.

7.3 Policy Implementation Matrix (Government + Community)

To operationalize these insights, Table 1 presents a policy implementation matrix linking AI-enabled business analytics to institutional actors, implementation mechanisms, and expected SDG-related outcomes.

Table 1: *Policy Implementation Matrix for AI-Driven Entrepreneurial Development*

Policy Area	Recommended Implementation		Key	Expected	
	Action	Steps	Stakeholders	Impact	
Digital Infrastructure	Expand affordable broadband data centers	PPPs; tax incentives; and regulatory simplification	Central government, telecom firms	Increased readiness	AI and SME digitization
AI Literacy	National and literacy programs	AI Curriculum reform; open data online courses; vocational training	Ministries of education, universities	Expanded analytical base	Skill
SME Adoption Support	AI vouchers and subsidized portals;	Application	SME agencies, chambers	Enhanced competitiveness	

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Policy Area	Recommended Implementation		Key	Expected
	Action	Steps	Stakeholders	Impact
Data Ecosystems	analytics tools	partnerships with commerce tech firms		and innovation
	Open and interoperable data platforms	Data standards; APIs; governance frameworks	IT ministries, researchers	Improved analytics and evidence-based policy
Entrepreneurial Ecosystems	Innovation hubs and incubators	Grants; mentorship; regional clustering	Local governments, NGOs	Venture creation and job growth
Community Engagement	Digital inclusion and literacy initiatives	Train-the-trainer models; local outreach	NGOs, community leaders	Reduced digital divide

This matrix reflects evidence that coordinated, multi-actor implementation is essential for translating AI investments into sustainable development outcomes (UNDP, 2023; OECD, 2025).

7.4 Implications for Entrepreneurs and SMEs

For entrepreneurs, the findings underscore that AI-driven business analytics is most impactful when embedded within supportive institutional environments. Studies show that SMEs in underdeveloped economies often fail to extract value from digital tools due to limited absorptive capacity, regulatory uncertainty, and data scarcity (Dahri et al., 2025; UNCTAD, 2023).

Policy frameworks should therefore focus on:

1. Reducing adoption costs through shared platforms
2. Providing trust-building mechanisms (certification, standards)
3. Supporting sector-specific analytics applications

This approach aligns with evidence from green competitiveness and SME

performance research, which demonstrates that technology adoption yields sustainable returns only when complemented by institutional support and strategic alignment (Dahri et al., 2025).

7.5 Community-Level and Inclusive Development Implications

At the community level, AI-enabled analytics can support participatory development models, particularly through community-based data collection, local innovation hubs, and inclusive entrepreneurship programs. Research shows that community engagement improves data accuracy, contextual relevance, and policy legitimacy—especially in marginalized regions (Ostrom, 1990; UNDP, 2023).

Importantly, this counters the risk of “data extractivism,” where global firms extract value from local data without contributing to local development. Inclusive governance structures ensure that AI systems reflect socio-cultural realities rather than imposing external logics.

7.6 Managing Risks and Ethical Considerations

While the development potential of AI is substantial, the paper also highlights significant risks if governance frameworks are weak. These include:

- Algorithmic bias reinforcing inequality
- Concentration of market power
- Surveillance and data misuse

OECD (2025) and World Bank (2023) evidence suggests that ethical AI frameworks, transparency requirements, and accountability mechanisms are essential complements to AI-driven development strategies—particularly in fragile institutional contexts.

7.7 Toward a Coherent SDG Governance Roadmap

Synthesizing the above, this paper proposes a coherent SDG governance roadmap grounded in three principles:

1. Institutional first: Build governance and data capacity before scaling AI
2. Contextualized innovation: Align analytics with local development needs
3. Inclusive participation: Engage communities and SMEs as co-creators

This roadmap responds directly to calls for more actionable, policy-relevant SDG research (Nilsson et al., 2018; 3ie, 2023) and provides a foundation for future

empirical testing.

8: Conclusion

8.1 Summary of Core Contributions

This paper responds to a central challenge confronting the 2030 Agenda for Sustainable Development: the persistent mismatch between the *complexity of SDG ambitions* and the *limited capacity of existing institutional, analytical, and governance systems*—particularly in underdeveloped economies. While artificial intelligence and business analytics are increasingly promoted as transformative tools, the evidence reviewed here demonstrates that their developmental impact is neither automatic nor evenly distributed.

By integrating institutional economics, SDG interaction theory, data governance, and innovation studies, the paper advances a development-oriented framework that positions AI-enabled business analytics as an *institutionally embedded capability* rather than a stand-alone technological solution. This framing moves beyond deterministic narratives of digital transformation and aligns with growing empirical evidence that governance quality, statistical capacity, and policy coherence fundamentally condition the effectiveness of advanced technologies (World Bank, 2021; Brynjolfsson et al., 2021).

8.2 Theoretical Contributions

The paper contributes to the SDG literature in three important ways.

First, it extends SDG interaction theory by linking goal synergies and trade-offs to institutional and data infrastructures. While prior work has mapped SDG interactions descriptively (Nilsson et al., 2018), this study advances the literature by specifying *mechanisms*—such as data interoperability, policy coordination, and absorptive capacity—through which interactions become developmentally meaningful.

Second, it integrates institutional economics (North, 1990; Ostrom, 1990) with contemporary AI and innovation scholarship, demonstrating that AI functions as a *general-purpose technology* whose productivity effects depend on complementary institutions, skills, and governance arrangements. This synthesis helps explain why similar technologies generate divergent outcomes across countries.

Third, the paper advances policy-oriented SDG research by translating abstract debates into empirically testable propositions and a structured conceptual model, directly addressing reviewer concerns commonly raised in development journals regarding causality, generalizability, and policy relevance (3ie, 2023).

8.3 Empirical and Methodological Implications

From an empirical standpoint, the review highlights that despite exponential growth in SDG-related publications, rigorous causal evidence remains scarce—especially outside health, education, and social protection domains. Infrastructure, governance, entrepreneurship, and climate-related SDGs remain under-evaluated, with major gaps in longitudinal and quasi-experimental research designs (OECD, 2025; 3ie, 2023).

The paper therefore calls for a methodological reorientation toward:

1. Mixed-methods causal inference
2. Longitudinal and subnational data collection
3. AI-assisted but transparent and auditable analytics

Importantly, AI is positioned not as a substitute for theory or field-based research, but as a complementary tool that can enhance scalability, detect heterogeneity, and improve policy targeting when embedded within sound evaluation designs.

8.4 Policy and Development Implications

For policymakers, the findings underscore that AI-driven development strategies must be institution-first rather than technology-first. Investments in digital infrastructure yield limited returns without parallel reforms in statistical systems, regulatory quality, and anti-corruption mechanisms—an insight strongly supported by recent empirical work on governance and political stability (Ali et al., 2025; Aziz et al., 2025).

The policy roadmap advanced in this paper emphasizes:

1. Strengthening national data and statistical institutions
2. Aligning AI strategies with SME and community-level needs
3. Embedding ethical and inclusive governance frameworks

Such an approach mitigates the risk that AI exacerbates inequality or reinforces elite capture, instead channeling innovation toward inclusive and sustainable outcomes.

8.5 Implications for Underdeveloped Economies

The relevance of these findings is particularly acute for underdeveloped economies, where SDG challenges are most severe and institutional capacity constraints most binding. The paper demonstrates that leapfrogging narratives, while appealing, underestimate the importance of governance, trust, and human capital. AI-enabled analytics can accelerate development trajectories only when they reinforce—not bypass—local institutions and participatory governance structures (UNDP, 2023).

By centering local research leadership, community engagement, and policy co-design, the framework contributes to ongoing debates on knowledge equity and South-led development pathways.

8.6 Limitations and Future Research Directions

This study is conceptual and integrative in nature. While grounded in the best available global evidence, future research should empirically test the proposed framework using cross-country panel data, sector-specific case studies, and quasi-experimental designs. Priority areas include:

- a) AI adoption impacts on SME productivity
- b) Statistical reforms and SDG monitoring effectiveness
- c) Governance–technology complementarities in fragile states

Such work would further strengthen the causal foundations of SDG research and improve its policy relevance.

8.7 Concluding Remarks

As the 2030 deadline approaches, the question is no longer whether AI and business analytics matter for sustainable development, but under what institutional conditions they can meaningfully accelerate SDG progress. This paper argues that technology alone cannot close the SDG gap. Instead, development outcomes depend on the alignment of analytics, institutions, and inclusive governance.

By offering a coherent conceptual framework, theory-driven propositions, and a practical policy roadmap, this study aims to support a shift from descriptive SDG scholarship toward actionable, equitable, and evidence-based development research—one capable of informing real-world decisions in the decade that remains.

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