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The role of LLM adoption in technological leapfrogging: Perspectives from the Global South

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Abstract

This conceptual paper explores the potential of large language models (LLMs) as enablers of technological leapfrogging in emerging economies, using theories of Dynamic Capabilities and Diffusion of Innovation as guiding frameworks. We propose a model that positions LLM adoption as a strategic tool for accelerating innovation and bypassing traditional stages of technological development and identify four key enabling factors—process re-engineering, innovation ecosystems, digital infrastructure, and government support—that interact to influence the successful integration of LLMs within organizations. Following the theory of Dynamic Capabilities the model suggests the importance of an organization's adaptive capacity: its ability to sense, seize, and transform in response to technological shifts. By situating LLM adoption within a broader systemic and institutional context as set out by the theory of Diffusion of Innovation, the model also highlights the critical role of collaborative networks and supportive policies in ensuring sustainable and inclusive AI-driven transformation. With a focus on Africa, and in particular Ghana, we aim to contribute to the discourse on digital transformation in the Global South and provide a foundation for future empirical research and policy development.

Keywords: Large Language Models, Technological Leapfrogging, Dynamic Capabilities Theory, Diffusion of Innovation Theory, Innovation Ecosystem, Digital Infrastructure, Emerging Economies

1 Introduction

Creative thinking and innovation in the deployment of emerging technologies can offer huge opportunities for economic advancement and labour productivity. It also entails the need to overcome some significant challenges, especially in resource-constrained contexts of the Global South. Such opportunities and challenges may play out differently in different national contexts. To facilitate ‘progress for all’ (Egosnet, 2024), there is therefore a need for greater understanding of the relationships between important factors in the application and adoption of emerging technologies such as generative artificial intelligence (GenAI) in a broad range of contexts, including, importantly, those of LMICs and the Global South (Adams et al, 2025).

Our paper explores the relationships between the adoption of Large Language Models (LLMs) and the potential for ‘technological leapfrogging’. Technological leapfrogging as acknowledged in the management literature is a process that can enable organizations to bypass intermediate stages of technological development to adopt advanced systems, enabling firms in LMICs to close the gap with developed economies (Soete, 1985). In Africa, this strategy has become increasingly important in addressing infrastructural and economic constraints. The continent’s unique challenges—such as underdeveloped infrastructure and limited access to traditional technologies—have made it a fertile ground for leapfrogging innovations (World Bank, 2017).

The advent of emerging technologies has revolutionized the business environment in the past decades. Amongst other things, these technologies have offered organizations the resources to enhance organizational learning, innovation and competitive advantage (Mugo & Macharia, 2020). Firms in developed countries are often better positioned to develop and utilize these technologies to boost performance as compared to counterparts in developing economies (Gartner et al, 2018). For organizations in the Global South, technological leapfrogging offers the potential to overcome infrastructural deficits, resource limitations, and skill gaps, enabling them to compete effectively in global markets (Heeks, 2018). This approach is increasingly relevant in an era where advancements such as large language models (LLMs) are redefining technological capabilities (Just, 2024).

Inspired by theories of Dynamic Capabilities (Teece et al, 1997; Teece, 2018) and Diffusion of Innovations (Rogers, 2003), we draw on a broad range of sources describing developments in the Global South to offer a conceptual model that seeks to elucidate the relationship between LLM adoption and technological leapfrogging by proposing mediating

and moderating roles for factors such as the potential for process re-engineering; the existence of effective innovation ecosystems; the state of development of digital infrastructure; and the existence of government support.

By focusing our exploration on sources from the Global South, we aim to investigate the applicability of existing theory in relation to Dynamic Capabilities and Diffusion of Innovation for the developing world and explore the potential need for extension or modification to such theories in this context. Weiss et al (2022) discussed the potential for research about new venture creation in Africa to challenge and extend theories developed primarily from studies in North America and Europe. Adarkwah et al (2023) noted that most authors of publications about ChatGPT that were available at the time of their study ‘were not from the African continent or were affiliated with international institutions’ and to address this deficit proposed ways to create technology trend awareness for academics from African countries like Ghana to transition from being ‘laggards’ to ‘early adopters’ in the terms of Rogers’ Diffusion of Innovations theory (Rogers, 2003). Hoffecker et al (2023) described how an approach to innovation ecosystem strengthening developed from case studies based in the United States was adapted and applied to an online ecosystem-strengthening process in Accra, Ghana and Adu (2024) presented a study of policies supporting the development and implementation of Artificial Intelligence, specifically in Ghana and Kenya, using a theory of deterritorialization to examine the different approaches of Microsoft and Google to localising global AI policies to Africa.

We seek to contribute to this growing body of work by presenting a conceptual model of ways in which LLMs can enable technological leapfrogging in resource-constrained contexts, proposing important mediating roles for organisations’ process re-engineering capabilities and innovation ecosystems, as well as moderating influences of digital infrastructure and government support. In this paper we present a review of existing research relating to the various elements of our model, with a focus on Africa, and in particular, where possible, on Ghana.

2 Theoretical background and context

2.1 Technological leapfrogging in resource-constrained environments

Technological leapfrogging means that companies and countries are able to jump towards new or more advanced technologies, thus allowing for potential development without having to invest as much in time and monetary resources as they would require with a linear approach (Comin & Hobijn, 2004). The leapfrogging concept is particularly salient in the context of developing countries, where the financial burden of investing in outdated technologies can impede progress. These nations are often able to take advantage of technological innovations that would have been out of reach under traditional developmental pathways (Moyo, 2020). For example, countries like China, India, and several African nations have capitalized on leapfrogging in diverse sectors such as telecommunications, renewable energy, and agriculture (Aker & Mbiti, 2010).

Telecommunications provide perhaps the best examples of leapfrogging, in the sense that many nations in Africa and Asia forwent the global growth of wired phone services and instead pursued mobile and wireless technologies which had lower costs in terms of infrastructure while also having greater reach (Aker & Mbiti, 2010). Another prominent example of leapfrogging is in mobile financial services. In Kenya, M-Pesa has enabled millions of people to access financial services without traditional bank accounts. This innovation has significantly improved financial inclusion, especially in rural and underserved regions (Kimenyi, 2015).

A leapfrogging strategy has also attracted much attention in the renewable energy sector. Countries that would have had to depend on fossil fuels and coal based generating stations as part of their development instead put in place solar, wind and other kinds of renewable energy technologies (Mulugetta et al., 2013). Africa has leapfrogged centralized energy systems by investing directly in renewable off-grid solutions. Companies like d.light and Off-Grid Electric offer solar kits that bring electricity to remote villages without the need for national grid expansion. These models not only address energy poverty but also support sustainable development and local entrepreneurship (Tremhost, 2023). In Rwanda and Kenya, decentralized energy systems have rapidly improved access, particularly in areas neglected by traditional infrastructure (Yousafzai & Matthee, 2021).

With regards to precision farming, biotechnology and other new sustainable agricultural technologies leapfrogging has had positive outcomes in the agricultural sector in many developing economies. These technologies can increase the yield of crops and enhance food security in locations where resources are limited (Hazell et al., 2007). Technological leapfrogging in agriculture is also seen in the adoption of ICT tools for improving productivity. Mobile platforms provide farmers with real-time market data, weather updates, and agricultural advice, improving decision-making and crop yields (Oughton, 2021). For example, platforms like iCow in Kenya and Esoko in Ghana help bridge the information gap between farmers and markets, although challenges such as digital illiteracy and uneven infrastructure still hinder broad-based adoption (Yousafzai & Matthee, 2021).

Finally, mobile health (mHealth) initiatives have used mobile platforms to provide essential healthcare services and health education, bridging gaps caused by insufficient healthcare infrastructure (Kimenyi, 2015; World Bank, 2017).

Although leapfrogging offers significant opportunities, it also presents various challenges. Some of the main obstacles in developing countries are the lack of infrastructure and financial resources necessary to support the widespread adoption of advanced technologies. Political instability and regulatory uncertainty in some regions can hinder the development and implementation of new technologies (Murphy, 2001) as can the absence of technical skills and the human capital to support the higher technological level which is expected from increased foreign direct investment (Gómez et al, 2017).

Ghana has been described as one of the KINGS of digital economy in Africa, by analogy with the Asian Tigers (Osiakwan 2017). The Republic of Ghana National Artificial Intelligence Strategy for 2023-2033 was drafted in October 2022 with the mission ‘To harness AI for inclusive growth across all sectors and to improve the lives of people in Ghana, becoming a trailblazer for AI leadership in Africa and beyond.’ (Ministry of Communications and Digitalisation, 2022). The AI ecosystem in Ghana has been mapped (Quaye et al, 2020; Ghana Innovation Journal, 2024) with Ghana’s AI market size in 2024 estimated at \$9.4 billion, making up about 2.4% of Africa's AI market and the country as a whole ranking favourably among the top African countries on the IMF’s AI adoption preparedness index, alongside South Africa, Rwanda, Tunisia and Morocco. However as of 2024, Quaye et al (2024) noted that less than 5% of the 300 SMEs they surveyed were using sophisticated technologies such AI. The

possibility of facilitating technological leapfrogging through the adoption of LLM technology is therefore an intriguing one.

2.2 Large Language Models (LLMs) and organizational transformation

Large Language Models (LLMs) have emerged as transformative tools, reshaping how organizations operate, innovate, and compete in the modern business landscape. LLMs, such as OpenAI's GPT series, leverage deep learning techniques to process and generate human-like text, enabling their application across various domains, including customer service, strategic planning, and content creation. These models are distinguished by their ability to analyze large datasets, draw meaningful insights, and perform tasks traditionally requiring human cognitive skills, making them integral to organizational transformation (Brown et al, 2020).

Large Language Models have demonstrated significant capabilities in a variety of applications and research areas, signaling a fundamental shift in how we approach artificial intelligence and its integration into various sectors (Berti et al., 2025; Vavekanand & Kumar, 2024). Their capacity to manage natural language has led to enhanced productivity and creativity, establishing them as indispensable assets in numerous professional and research contexts (Huang et al., 2024).

LLMs have been utilized to automate routine tasks, such as drafting reports, managing communications, and performing data entry, thereby freeing employees to focus on higher-value activities and driving productivity gains (Lashkevich et al, 2024). In customer-facing roles, they have enabled organizations to handle high volumes of customer interactions while maintaining consistency and empathy, contributing to improved satisfaction and loyalty (Rajpurkar et al., 2018). Finally, in the pharmaceutical and legal industries, LLMs facilitate research by summarizing vast scientific literature and legal documents, significantly reducing the time and cost of knowledge acquisition (Zhou et al, 2024). Such capabilities empower organizations to stay at the forefront of industry developments, ensuring long-term resilience and growth.

The integration of Large Language Models into multi-agent systems is further revolutionizing the development of sophisticated process engineering solutions, as these systems can autonomously address complex challenges (He et al., 2024). As an example, the capability of LLMs to process extensive datasets and derive meaningful insights from them, facilitating well-informed decision-making and the formulation of evidence-based strategies,

has also been said to constitute a pivotal contribution to the progression of pharmaceutical supply chain management (Aguero & Nelson, 2024).

However, integrating LLMs into organizational workflows also presents challenges, particularly regarding ethical considerations, data privacy, and workforce adaptation. Organizations must address employee apprehensions about job displacement and skill obsolescence by emphasizing reskilling programs and fostering a collaborative human-AI work environment (Brynjolfsson & McAfee, 2022). Additionally concerns about biases in training data and model outputs highlight the need for robust governance frameworks to ensure fairness and transparency (Bender et al., 2021). Work on this last point, addressing the specifics of LLM performance with African languages has begun (Adebara et al, 2022; Adebara et al, 2025; Alhanai et al, 2025) but more is needed.

2.3 Diffusion of Innovations and Dynamic Capabilities

Dynamic Capabilities theory and Diffusion of Innovation theory provide complementary lenses for understanding the adoption and integration of transformative technologies like Large Language Models in organizations.

As Rogers (2003) explains, Diffusion of Innovation theory elucidates how innovations are communicated, adopted, and spread within and across social systems. This theory identifies key factors influencing adoption, including relative advantage, compatibility with existing systems, perceived complexity, trialability, and observability (Foster et al., 2020). These elements can help explain how organizations perceive and integrate new technologies like LLMs. For instance, the relative advantage of LLMs lies in their ability to streamline operations and drive efficiency, while compatibility and trialability influence how easily organizations can adopt and experiment with these models (Foster et al., 2020). Moreover, Diffusion of Innovation Theory also highlights the importance of early adopters in promoting innovation within a network, which is crucial for understanding the broader adoption of LLMs in various industries. The intrinsic characteristics of an innovation, encompassing aspects such as its complexity and its congruence with existing operational frameworks, significantly shape the dynamics of its assimilation and acceptance within a given context (Rogers, 2003).

Dynamic Capabilities theory, introduced by Teece et al (1997), complements this perspective by emphasizing an organization's ability to sense opportunities, seize them effectively, and reconfigure resources to adapt to rapidly changing environments. This theory

underscores the importance of organizational agility and the capacity to innovate as critical drivers of competitive advantage. In the context of LLMs, Dynamic Capabilities enable organizations to identify the strategic value of these technologies, integrate them into existing workflows, and continually refine their use to meet evolving business demands. The theory highlights that successful technological adoption is not merely about acquiring resources but also about the ability to align and transform them to achieve strategic objectives.(Arifin & Frmanzah, 2015; Jamil et al., 2025; Rosenbäck & Eriksson, 2024). Moreover, the theory posits that organizations must develop specific mechanisms for learning and adaptation, including knowledge management systems and experimentation protocols, to fully leverage new technologies. These Dynamic Capabilities are essential for creating sustainable competitive advantages in the face of technological disruption, as they allow organizations to proactively respond to market changes and capitalize on emerging opportunities.(Cyfert et al., 2021; Ellström et al., 2021)

We propose that the combination of Diffusion of Innovation Theory and Dynamic Capabilities Theory can provide a robust framework for analyzing organizational transformation through technology and elucidating the organizational dynamics underpinning the adoption and deployment of LLMs. While Dynamic Capabilities theory focuses on the internal competencies required to adapt and innovate, Diffusion of Innovation theory addresses the external social and systemic factors that drive the spread of technology. Their intersection becomes particularly relevant when studying how organizations in resource-constrained settings leverage LLMs to bridge technological gaps and foster innovation. This requires a multifaceted approach that considers not only the technology itself but also the organizational and systemic conditions that enable its successful adoption and diffusion. In the following section, we outline some of what we believe to be the key dimensions for consideration in such an approach.

3 Routes to technological leapfrogging through adoption of LLMs: A thematic review

3.1 LLM adoption and technological leapfrogging

The adoption of large language models represents a strategic avenue for technological leapfrogging, particularly in emerging economies. Rather than following the linear progression of technological evolution, organizations can bypass intermediate stages and integrate advanced AI systems to solve complex problems, such as real-time language translation or automated content generation. This leap is most impactful in contexts where legacy systems

are underdeveloped or altogether absent, allowing firms to build modern digital infrastructures from the ground up. Such capabilities are especially relevant in regions where traditional technological infrastructure is lacking, offering a chance to establish state-of-the-art systems without the encumbrance of outdated technologies (Alper & Miktus, 2019; Chleuh, 2021), as will be further discussed below.

Viewed through the lens of Dynamic Capabilities Theory, LLM adoption reflects an organization's ability to sense emerging technological trends, seize novel opportunities, and transform internal processes and competencies to achieve competitive advantage. Organizations that successfully deploy LLMs demonstrate agility in reconfiguring existing resources, embedding AI into workflows, and upskilling employees to work alongside intelligent systems. This agility is not just a technical matter—it signals a deeper organizational capacity for strategic learning, adaptation, and renewal.

The integration of LLMs into healthcare exemplifies technological leapfrogging by enabling more efficient clinical practices, improved patient care, and better health outcomes through technologies like transfer learning and domain-specific fine-tuning (Karabacak & Margetis, 2023). The adoption of LLMs allows healthcare providers in developing regions to overcome infrastructure limitations by providing sophisticated diagnostic and treatment support via mobile devices. This can lead to more equitable access to healthcare, irrespective of geographical constraints or resource scarcity.

The Diffusion of Innovation theory helps to explain how LLMs, as a disruptive technology, spread through a population or an industry. Early adopters often include technologically advanced or forward-thinking organizations that recognize the potential benefits of LLMs and are willing to take risks. This pattern of adoption not only shapes competitive dynamics but also influences broader societal trends, as early adopters demonstrate the technology's viability and encourage wider acceptance. (Huang et al., 2024; Lambiase et al., 2025; Yao & González-Vélez, 2025).

Proposition 1: Higher levels of LLM adoption are positively associated with greater technological leapfrogging in organizations and nations.

3.2 Mediating effect of process re-engineering

The integration of Large Language Models (LLMs) and the concept of technological leapfrogging hold considerable promise for advancing digital transformation in Africa.

Empirical studies suggest that organizations using AI technologies, including LLMs, have significantly enhanced their operational performance, thereby enabling them to leapfrog competitors in their industries (Willcocks & Lacity, 2016). For example, the application of LLMs in supply chain management has streamlined operations, enabling firms to achieve unprecedented levels of efficiency (Chui et al., 2018).

However, the successful adoption of these technologies necessitates comprehensive process re-engineering to align organizational structures, workflows, and cultural dynamics with the capabilities of LLMs. Process re-engineering, which involves redesigning business processes for efficiency and effectiveness, is a key mechanism through which LLM adoption impacts technological leapfrogging. Effective process re-engineering can facilitate the adoption of LLMs, which in turn can drive technological leapfrogging by enabling more efficient and innovative practices. For example, the integration of LLMs into business processes can automate routine tasks, allowing organizations to focus on more strategic activities, thereby accelerating development. In terms of Dynamic Capabilities theory, the capability of process re-engineering can be seen as a dynamic capability for creating value by transforming existing business processes.

Proposition 2: Process re-engineering mediates the relationship between LLM adoption and technological leapfrogging, as LLM-driven improvements in processes help achieve advanced technological capabilities.

3.3 Mediating effect of innovation ecosystems

Innovation ecosystems, comprising networks of firms, research institutions, and government agencies, play a pivotal role in facilitating technological progress. In terms of Diffusion of Innovation, ecosystems provide many of the communication channels and social systems through which innovations may be diffused. In terms of Dynamic Capabilities theory, ecosystems can help organisations to sense changes in the business environment and thereby to identify opportunities.

Studies have shown that ecosystems with active engagement between stakeholders can amplify the benefits of LLMs by fostering innovation diffusion and collective learning (Adner, 2006). For instance, the adoption of AI-driven platforms in healthcare ecosystems has improved patient outcomes by integrating LLMs into diagnostic tools and resource allocation systems (Topol, 2019). More recently, following their mapping of potentials and limitations of

generative AI to address socio-economic challenges in LMICs Adams et al (2025) have called for ‘adequately funded enabling environments for local and responsible AI innovation to thrive’.

However it is also crucial to note that the concept of technological leapfrogging is not universally accepted as a guaranteed path to development (Ojo & Ogunleye, 2021). Some scholars contend that without sufficient investment in foundational education and infrastructure, the adoption of advanced technologies may exacerbate existing inequalities, leading to a widening digital divide (Sorj, 2008). Aggarwal et al (2021) have noted how persistently low digital literacy levels and a scarcity of locally relevant digital content pose substantial challenges to widespread adoption. Socio-cultural factors also wield considerable influence, as deeply rooted traditional practices and linguistic diversity can hinder the seamless integration of novel technologies (Sigama & Kalema, 2022).

Proposition 3: Innovation ecosystems mediate the relationship between LLM adoption and technological leapfrogging, enabling LLM adoption to drive transformative outcomes more effectively through ecosystem interactions.

3.4 Moderating effect of digital infrastructure

The emergence of LLMs such as ChatGPT, BLOOM, and SERENGETI has significantly improved language processing, data analysis, and decision-making across sectors. In Africa, as set out above, LLMs have begun to influence innovation efforts, particularly in areas such as health, education, and governance (Adebara et al., 2022). However, these models require high levels of digital readiness, suggesting that the quality of a region's digital infrastructure may be a crucial determinant of impact.

Digital infrastructure—which includes broadband internet, cloud platforms, data centers, and power reliability—forms the bedrock for sustainable innovation. Empirical evidence from 28 African countries between 2011 and 2019 confirms that digital infrastructure has a significant positive impact on innovation outputs, especially when aligned with human capital development (Kabbiri et al., 2024). As an example, Rwanda's Vision 2020 strategy emphasizes investments in digital infrastructure and human capital, leading to advancements in sectors like drone technology (CSIS, 2020). The World Bank (2023) also identifies internet access as a key driver of innovation, employment, and inclusion in Africa's digital transformation strategy.

LLMs such as SERENGETI, which support over 500 African languages, demonstrate Africa's potential in building localized AI technologies (Adebara et al., 2022). However, deployment across the continent remains uneven. While countries like South Africa, Kenya, and Nigeria have more advanced infrastructure, others lack sufficient cloud access, stable power, and affordable internet, hindering meaningful LLM adoption and experimentation.

Critical infrastructure deficits, including inadequate broadband access and unreliable electricity, severely limit the scalability of many digital technologies (Ndlovu & Newman, 2020). For an example of this effect from a particular sector we can look to Africa's education sector, where leapfrogging is playing a transformative role. Startups like Eneza Education deliver curriculum-aligned lessons via SMS, allowing students without internet access or smart devices to learn affordably (The Perspective, 2019). These technologies are crucial in overcoming barriers like teacher shortages and lack of classroom resources in rural areas. However, their success is closely tied to mobile network coverage (Kimenyi, 2015).

A strong digital infrastructure facilitates the seamless deployment of LLMs, allowing innovation ecosystems to maximize their potential (Goldfarb & Tucker, 2019). Conversely, poor digital infrastructure has been shown to hinder the adoption of AI technologies, limiting their impact (Bughin et al., 2018), and Quaye et al (2024) have found that poor technology enabling infrastructure is among the top five barriers to technology adoption by SMEs in Ghana. Björkegren et al (2025) have argued that AI use is much less expensive than the use of web search, in terms of data usage, meaning that the impact of digital infrastructure quality on the uptake of AI may be less than it was for previous technologies. However the economic disparities between developed and developing nations still seem likely to hinder the latter's ability to invest in and sustain good quality technological infrastructure, making it difficult for innovation ecosystems in these contexts to make best use of emerging LLM technologies.

In summary we propose that the relationship between LLM adoption and innovation ecosystems is moderated by the quality of digital infrastructure. In regions with strong infrastructure, LLMs accelerate research, entrepreneurial ventures, and public sector reform. Conversely, in infrastructure-poor areas, these models become inaccessible or underutilized. For instance, Africa holds less than 1% of global data center capacity despite comprising over 18% of the global population (Brookings Institution, 2025). This imbalance undermines equitable access to LLM capabilities.

Proposition 4: The relationship between LLM adoption and innovation ecosystems is stronger when digital infrastructure is good, and weaker when digital infrastructure is poor.

3.5 Moderating effect of government support

Africa's potential to leapfrog traditional development stages through technology adoption is well-documented. However, the success of such leapfrogging is not solely dependent on technological availability but also on the strength of innovation ecosystems and the extent of government support. Here we examine the moderating role of government support in the relationship between innovation ecosystems and technological leapfrogging in Africa.

Innovation ecosystems, comprising networks of institutions, firms, and policies, are crucial for fostering technological advancement. In Africa, the emergence of tech hubs, innovation centers, and startups has created a conducive environment for innovation. For instance, Nigeria has established over 80 innovation hubs, attracting venture capital and supporting entrepreneurs (BCG, 2021). Such ecosystems have enabled the development and adoption of technologies like mobile banking and renewable energy solutions, facilitating leapfrogging in sectors like finance and energy.

Government support plays a pivotal role in strengthening innovation ecosystems and enabling technological leapfrogging. Policies that invest in infrastructure, education, and research and development (R&D) are essential. For example, Kenya's Science, Technology & Innovation Act of 2012 and the establishment of science and technology parks have been instrumental in promoting a knowledge-based economy (CIO Africa, 2022). There have been many calls in recent years for government support in this context. For example Adarkwah et al (2023) call for policymakers to promote 'technological awareness' to enable a transformation of education in Ghana through the use of generative AI; El Louadi (2025) advocate for investing in data in order to foster digital literacy and preserve culture; and Quaye et al (2024) noted how 60% of SMEs in Ghana that were in receipt of Presidential Business Development Support had adopted technologies such as social media, mobile banking and e-commerce, while only 50% of those who were not in receipt of this support had done so.

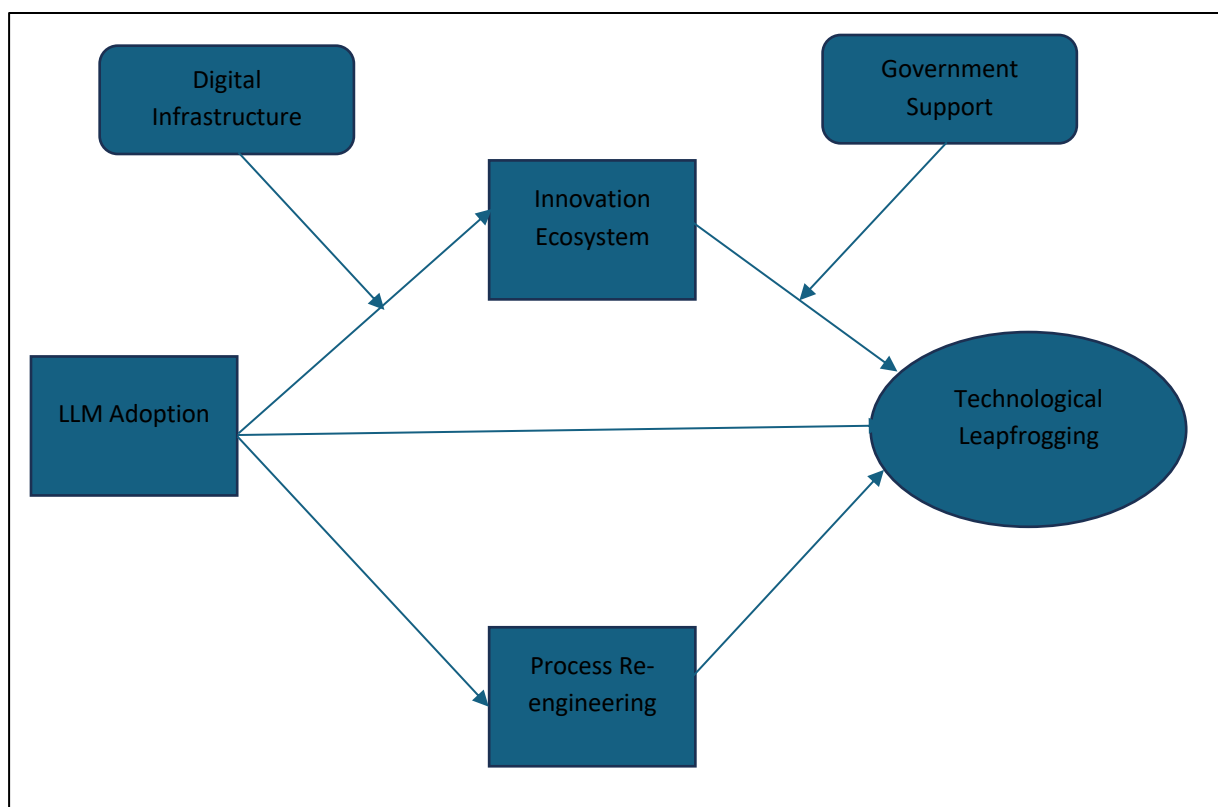
We argue that the relationship between innovation ecosystems and technological leapfrogging is significantly moderated by government support. In countries with strong government backing, innovation ecosystems are more effective in facilitating leapfrogging.

Conversely, in the absence of substantial government support, innovation ecosystems may struggle to achieve their full potential.

Government support, in the form of policies, funding, and incentives, positively influences the capacity of innovation ecosystems to drive technological leapfrogging. Studies indicate that government-backed initiatives, such as subsidies for AI adoption and investments in digital literacy, accelerate the deployment of advanced technologies (Mazzucato, 2015). Conversely, a lack of government support can constrain innovation ecosystems, reducing their ability to achieve leapfrogging outcomes (Geels, 2002).

Proposition 5: The relationship between innovation ecosystems and technological leapfrogging is stronger when government support is high, and weaker when government support is low.

Figure 1: Conceptual Model



4 Discussion

This conceptual model aims to represent the ways in which the adoption of large language models can drive technological leapfrogging, particularly within emerging economies.

Underpinned by the theories of Dynamic Capabilities and Diffusion of Innovation, the model positions LLM adoption as a catalyst, enabling firms to sense new technological opportunities, seize them through innovation, and transform internal operations for sustained competitiveness. By leveraging LLMs, organizations in resource-constrained settings can bypass intermediate stages of technological development and implement advanced AI tools that enhance productivity, communication, and decision-making. This process accelerates digital transformation and redefines competitive dynamics across sectors, underscoring the importance of creating environments that foster continuous learning and adaptation.

We argue that a critical enabler in this transformation is process re-engineering. Organizations must adapt their internal workflows, restructure inefficient operations, and align decision-making processes with AI capabilities to unlock the full potential of LLMs. This reconfiguration reflects an organization's transformation capability and is essential to embedding AI systems into the core of operations. Consequently, LLM adoption must go hand-in-hand with organizational change management strategies and capacity-building efforts. Simply acquiring the technology is insufficient; firms must also foster adaptive cultures and invest in employee upskilling to ensure successful integration.

We believe the innovation ecosystem also plays a pivotal external role in supporting LLM adoption. A strong network of research institutions, private firms, startups, and regulatory bodies enhances an organization's ability to sense emerging trends and collaborate on AI applications. Policymakers and ecosystem actors, therefore, need to foster open innovation environments, support cross-sectoral partnerships, and invest in platforms that promote AI knowledge exchange. Without such an ecosystem, firms may lack the external stimuli and resources required for effective technology adoption and scaling.

Digital infrastructure is another foundational element in our model. For LLMs to be effectively deployed, organizations must have access to robust technological backbones, including high-speed internet, cloud computing, and secure data systems. Thus, governments and development agencies must prioritize digital infrastructure development in national innovation strategies. Without these basic enablers, attempts to adopt sophisticated AI tools may fail, perpetuating digital divides rather than closing them.

Finally, government support is conceptualized as an important enabler. Through regulation, funding, data policies, and strategic direction, governments shape the conditions

under which LLMs are adopted. Proactive and supportive policies can de-risk innovation and encourage responsible AI use, especially in high-stakes domains such as education, health, and finance. This implies that government engagement should go beyond rhetoric to provide clear policy frameworks, funding mechanisms, and monitoring systems that promote ethical and inclusive AI deployment.

Our model suggests that the impact of LLMs depends not only on their technical sophistication but also on the organizational, infrastructural, and institutional conditions in which they are deployed. It has several practical implications. For business leaders, it offers a roadmap for aligning internal capabilities with emerging technologies. To facilitate technological leapfrogging through LLM adoption, the model suggests embracing the potential of internal process re-engineering initiatives and participating in relevant innovation ecosystems. For policymakers, the model highlights the importance of funding as well as regulatory and infrastructural readiness. For scholars, it provides a framework to explore empirical relationships between AI adoption and organizational transformation in the Global South.

To empirically test our model we plan to collect both quantitative and qualitative data from a sample of SMEs in Ghana operating across multiple sectors of the economy including e-commerce, education, digital marketing, freelance/digital services and customer services. For the quantitative component, we plan an online survey with an expected response rate of at least 75%, targeting 150 – 200 SMEs reached through trade associations including Ghana Club 100 and the Association of Ghana Industries (AGI). For the qualitative component, we plan around 30 in person semi-structured interviews and/or focus group discussions with government agencies and regulators, policy makers and leaders of incubators and accelerators.

5 Conclusion

This conceptual paper examines the transformative potential of large language models in driving technological leapfrogging, particularly within emerging economies, through the lens of Dynamic Capabilities and Diffusion of Innovation Theories. By framing LLM adoption as a strategic enabler of innovation, the study highlights how organizations can bypass traditional stages of technological progression and embrace cutting-edge digital solutions to enhance competitiveness and developmental outcomes. The proposed model identifies key enablers—

process re-engineering, innovation ecosystems, digital infrastructure, and government support—as critical to realizing the full benefits of LLMs. These elements interact to shape an organization’s ability to sense new opportunities, seize them through innovation, and transform internal processes in response to rapid technological change. Each factor plays a distinct yet interconnected role in facilitating successful AI integration, ensuring that leapfrogging is both sustainable and inclusive, and fostering environments conducive to innovation. Importantly, the study moves beyond the technical capabilities of LLMs to emphasize the broader systemic and institutional conditions required for their effective deployment. It underscores that while LLMs hold great promise, their impact will ultimately depend on how well organizations and governments build Dynamic Capabilities that foster continuous learning, adaptability, and responsible innovation. In sum, this paper contributes to the ongoing discourse on AI adoption in the Global South by offering a theory-driven framework that links advanced technologies with developmental strategies. It provides a foundation for future empirical studies and policy interventions aimed at unlocking the full potential of LLMs to accelerate technological progress, bridge digital divides, and support inclusive economic transformation.

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