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ARTIFICIAL INTELLIGENCE READINESS AND ORGANIZATIONAL ADAPTABILITY IN POST-DIGITAL ECONOMIES: EVIDENCE FROM EMERGING AFRICAN MARKETS: A CASE STUDY OF NIGERIA

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Abstract

The rapid proliferation of artificial intelligence (AI) is transforming organizational structures, competitive dynamics, and strategic priorities across the global business landscape. However, existing scholarship on AI readiness and organizational adaptability is largely derived from advanced economies, with limited attention to the institutional realities and adaptive capacities of firms in emerging African markets. This study addresses this gap by examining AI readiness and organizational adaptability in Nigeria, Africa's largest economy by GDP and most populous nation. Drawing on Dynamic Capabilities Theory, the Technology–Organization–Environment (TOE) framework, and Institutional Theory, the study develops an integrated, multi-level framework for understanding AI readiness across technological infrastructure, human capital, organizational culture, regulatory environments, and macroeconomic conditions. Evidence was obtained through fieldwork involving Nigerian commercial banks, telecommunications firms, fast-moving consumer goods (FMCG) companies, and public sector agencies, complemented by industry reports, regulatory publications, and academic literature published between 2015 and 2026. Findings reveal uneven patterns of AI adoption. While large, internationally connected organizations are increasingly deploying AI in customer relationship management, credit-risk assessment, and operational analytics, most organizations particularly SMEs remain constrained by inadequate infrastructure, talent shortages, and weak institutional support. Five factors consistently predict organizational adaptability: digital infrastructure adequacy, leadership AI literacy and strategic vision, the availability and retention of AI talent, regulatory clarity, and a culture of organizational learning. The study advances Dynamic Capabilities Theory by conceptualizing AI readiness as a higher-order capability in resource-constrained contexts and proposes the construct of contextually adaptive AI readiness. It concludes by offering practical recommendations for policymakers, organizational leaders, and development partners pursuing inclusive and sustainable AI transformation in Nigeria and comparable African economies.

Keywords: Artificial Intelligence Readiness; Post-Digital Economy; Emerging Markets; Digital Transformation; Technology Adoption; Institutional Theory

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Introduction

The global economy is at an inflection point. The convergence of exponential gains in computing power, proliferation of connected devices, democratization of cloud computing, and maturing of machine learning has led to what scholars increasingly refer to as the post-digital era, a period in which digital technologies are no longer exceptional or differentiating, but act as foundational infrastructure for economic activity, organizational structure and competitive strategy (Parviainen et al., 2022; Westerman, Bonnet & McAfee, 2019). In this shift, artificial intelligence has become the defining enabling technology of the age. It can simulate, augment and in narrow domains exceed human cognition and in doing so rewrite the logic of production, service delivery and decision-making.

The macro-economic stakes are hard to overstate. According to the McKinsey Global Institute (2023), AI could contribute a further \$13 trillion to the global output by 2030, and PwC (2023) puts it at \$15.7 trillion. But these gains are uneven geographically. North America, Europe and East Asia regions with mature infrastructure, large pools of talent and settled regulatory regimes – are expected to capture most of the expected expansion, with Sub-Saharan Africa projected to take a modest share (African Development Bank, 2022). That is a sobering prospect for a region that has some of the world's most dynamic economies and some of the most pressing development challenges.

Nigeria has a paradoxical role in this landscape. It is Africa's largest economy by nominal GDP of about \$477 billion in 2023 (World Bank), its most populous nation (an estimated 220 million people in 2024) and home to one of its most vibrant technology ecosystems. Venture capital into the Lagos "Silicon Lagoon" topped \$1.8 billion from 2020-2023 (Partech Africa, 2023), and the city has become a hub for start-ups, fintechs and digital-service providers. A young and increasingly educated and digitally literate population – median age of around 18.4 years – is a huge consumer market and potential talent base for AI-intensive industries.

This potential is tempered by a formidable set of structural constraints: chronic power shortages, uneven broadband penetration, limited technical education and research capacity in AI-relevant fields, regulatory architecture still in the making, and profound socio-economic inequalities that shape both demand for AI and its distributional effects (Ndung'u & Signé, 2020; Asongu & Nwachukwu, 2016). How firms navigate this terrain of opportunity and constraint is not just an academic question, it

has real urgency for managers, policy makers and development practitioners.

There has been considerable attention on the level of technological, human, organizational and strategic resources an organization has available to adopt, embed and exploit AI – AI readiness (Bughin et al., 2018; Fountaine, McCarthy & Saleh, 2019; Alsheibani, Cheung & Messom, 2018). However, the dominant conceptualizations were largely constructed in advanced economies, raising real questions about their validity in contexts such as Nigeria where the foundational conditions are very different from what the mainstream literature assumes (Marda & Narayan, 2020; Cenfetelli & Schwarz, 2011). In response, this paper develops a contextually grounded, theoretically integrated account of AI readiness and adaptability in Nigeria that extends existing frameworks to capture the dynamics of a developing African market.

Statement of the Problem

AI is widely recognized as an enabler of competitive advantage and growth in the post-digital economy. However, the conditions that determine AI readiness and adaptability in Nigeria are poorly understood for several reasons. First, there is an evident empirical gap. Most studies on AI readiness and adoption are based on data from the United States, the European Union, China and other advanced economies with little focus on African contexts and Nigeria in particular. This bias is no small inconvenience – it replicates a structural inequality in knowledge production with direct consequences on practice and policy in African markets (Adesola & Arthur, 2020; Asongu, Nnanna & Acha-Anyi, 2020).

Second, readiness frameworks tend to privilege technological and infrastructural factors over the institutional, cultural and political-economic conditions that matter most in Nigeria. Assessments calibrated to conditions not faced by local organizations and policy makers risk being misled (Datta, 2018; Meissner, Polt & Vonortas, 2017). Third, the relationship between AI readiness and organizational adaptability, a firm's ability to reconfigure its structures, processes and strategies as its environment changes, has not been studied systematically in the post-digital context of emerging African markets. The relationship is theoretically complex and empirically sparse, especially in terms of how resource-constrained firms develop the dynamic capabilities required not only to adopt AI but to turn it into sustainable advantage (Teece, 2018; Phan & Wood, 2020).

Thus, the study raises a pertinent and practically important question: what are the determinants, dimensions and organizational consequences of AI readiness in the Nigerian post-digital economy and how do they shape the adaptive capacities of Nigerian organizations?

Objectives of the Study

The study has five objectives:

1. to examine the conceptualization of AI readiness and organizational adaptability in post-digital economies and the extent to which such concepts travel to emerging African markets;
2. to develop an integrated framework for Nigeria drawing on Dynamic Capabilities Theory, the TOE framework and Institutional Theory;
3. to empirically assess the current state of AI readiness in key sectors and identify its determinants, barriers and enablers;
4. to explore the relationship between readiness dimensions and adaptability outcomes and how Nigerian firms can use AI to strengthen dynamic capabilities; and
5. to provide recommendations to leaders, policymakers and development partners to advance AI-enabled transformation.

Questions for Research

1. How can the institutional, infrastructural and organizational characteristics of the Nigerian post-digital economy be conceptualized and operationalized towards the development of AI readiness?
2. What are the key drivers of AI readiness of Nigerian organizations and how do they vary across sectors, sizes and ownership?
3. The extent to which AI readiness influences organizational adaptability in Nigeria's post-digital economy.
4. What strategic, organizational and policy interventions are likely to be most effective in promoting AI readiness and adaptability in Nigeria and similar African markets?
5. What are the recommendations to leaders, policymakers and development partners to advance AI-enabled transformation

Importance of the Study

The study extends and contextualizes artificial intelligence, dynamic-capabilities and organizational-transformation scholarship for emerging markets and introduces the construct of contextually adaptive AI readiness, which applies beyond Nigeria to the

general problem of building AI-enabled capacity under resource and institutional constraints. Empirically, it offers a systematic and evidence-based view of the AI landscape of Nigerian organizations operating in multiple sectors and contributes to an ever-growing body of African-centric management scholarship that pays attention to the idiosyncratic dynamics of business in Africa (Zoogah, Peng & Merchant, 2015; Acquaaah, 2016; Lituchy, Galperin & Punnett, 2017). In practice, its findings inform decisions of managers considering AI adoption, regulators working out governance frameworks and development partners designing capacity-building programmes – all of which are timely, given the urgency of evidence-based AI policy in Africa.

Literature Review

Understanding Artificial Intelligence in Business Settings

In contemporary business environments, AI encompasses a wide and rapidly evolving range of techniques designed to accomplish tasks that would involve learning, reasoning, problem-solving, perception or language understanding if performed by humans (Russell & Norvig, 2021; LeCun, Bengio & Hinton, 2015). For organizations, three types are relevant: narrow (weak) AI, designed for a specific task such as machine translation, recognizing images, credit scoring or demand forecasting; general AI, a hypothetical system with broad human-level cognition that has not yet been realized; and the rapidly emerging category of large language models and foundation models, which, while still narrow in a technical sense, exhibit unusual flexibility across linguistic and reasoning tasks (Brown et al., 2020; Bommasani et al., 2021).

Almost all adoption by organizations today is in the narrow-AI category, delivered through machine learning, deep learning, natural language processing, computer vision and robotic process automation. They require different data infrastructure, technical talent, process design and governance (Davenport & Ronanki, 2018; Brynjolfsson & McAfee, 2017). AI's nature as a general-purpose technology like electricity or the internet, it is cross-cutting, raising productivity across the board and spawning waves of complementary innovation (Cockburn, Henderson & Stern, 2018; Trajtenberg, 2019) heightens that significance.

The business literature has documented the effects of AI on functions. It allows for hyper-personalization, churn prediction, sentiment analysis

and intelligent chatbots in marketing and customer management, thus revolutionizing the economics of acquisition and retention (Davenport, Guha & Grewal, 2019; Rust & Huang, 2021). In operations and supply chains, machine learning supports predictive maintenance, demand sensing, dynamic routing and automated quality control (Choi, Wallace & Wang, 2018; Queiroz et al., 2021). AI is transforming credit-risk assessment, fraud detection, algorithmic trading and regulatory compliance in finance, which is of particular relevance to Nigeria (Buchanan, 2019; Cao, 2022). And in human-resource management it is transforming talent acquisition, performance management and workforce planning with effects on structure and employment relations (Tambe, Cappelli & Yakubovich, 2019; Pan & Froese, 2023).

This proliferation comes with well-documented risks: algorithmic bias (Barocas, Hardt & Narayanan, 2019), limited transparency and explainability (Adadi & Berrada, 2018), data-privacy and security exposure (Taddeo, McCutcheon & Floridi, 2019), and labour displacement with distributional consequences (Acemoglu & Restrepo, 2018). In Africa, these are amplified by other considerations: the possibility of re-establishing colonial data dependencies (Couldry & Mejias, 2019; Birhane, 2021); the linguistic and cultural insularity of systems built on predominantly English-language, Western-centric data (Hovy & Lavid, 2021); and the threat that automation forecloses the labor-intensive industrialization pathways that have historically driven structural transformation (Rodrik, 2018; UNCTAD, 2022).

The post-digital economy: contours of theory

The post-digital economy is a popular term used to describe the current phase of digital transformation (Parviainen et al., 2022; Cearley, Jones & Chandrasekaran, 2019). Digitization is the transformation of analogue processes into digital form, while digital transformation is the organizational change that digitization enables. The post-digital condition describes the point at which digital technologies are so embedded in organizational and social infrastructure that “digital” no longer differentiates, it is simply the baseline of organizational existence (Westerman, Bonnet & McAfee, 2019; Sebastian et al., 2017).

In that context the strategic question is not whether to embrace digital technologies but how to deploy them creatively for distinctive value. AI is at the heart of this reconfiguration because it offers a new class of capability – learning from data and making

increasingly autonomous decisions beyond the automation and information processing of earlier technologies (Huang, De Winter & Kim, 2021; Iansiti & Lakhani, 2020). Bughin and Hazan (2017) call AI a “meta-technology” that improves the efficiency of other technologies and processes, and Brynjolfsson and McAfee (2017) compare its productivity potential to the Industrial Revolution.

The idea has particular unexplored implications for emerging markets. Many African economies have witnessed leapfrogging, which involves the compression or partial skipping of successive technological waves, rather than sequentially passing through them (Aker & Mbiti, 2010; Asongu & Le Roux, 2017). The best example is mobile money, which in much of the region has leapfrogged branch-based banking infrastructure. In the African context, therefore, the post-digital framework should be considered analytically separate from the sequential adoption stories of the advanced-economy literature and should expressly account for local institutional and infrastructural realities.

Crucially, the post-digital economy is not a single global condition, but an aspiration and trajectory which different economies can approach at different speeds and along different institutional paths. For Nigeria, the transition is at once a significant opportunity, the opportunity to build AI-enabled capacity unencumbered by legacy infrastructure, and a major obstacle, given the need to build AI-ready organisations against a backdrop of resource constraints and structural vulnerability. This tension between potential for leapfrogging and structural constraint runs through the analysis that follows.

Dimensions and Frameworks of AI Readiness

Over the last decade, there has been an increasing academic interest in AI readiness, but the literature remains fragmented and the construct is operationalized inconsistently. Drawing on previous work on technology readiness (Parasuraman, 2000) and organizational readiness for change (Holt et al., 2007), readiness frameworks generally focus on the extent to which an organization has the resources, capabilities and conditions to successfully adopt and benefit from artificial intelligence (AI). Several are worth mentioning:

In an influential McKinsey report, Bughin et al. (2018) operationalize readiness in five dimensions: AI strategy, organizational capabilities, data assets, technological infrastructure, and AI culture. The framework is well-cited, but largely built on surveys of large advanced-economy firms, so care is needed in its transfer to Nigeria. A richer conceptual model is proposed by Alsheibani, Cheung and Messom

(2018), based on TOE, which distinguishes between organizational, technological and environmental factors. These are top-management support, learning culture and inter-organizational networks, data quality, system integration and cybersecurity, and environmental conditions such as competitive pressure, regulatory support and access to talent. It recognises the organisational context but it is not looking specifically at emerging markets.

National indices, such as the Oxford Insights Government AI Readiness Index and the ITU assessment, assess readiness at the country level, looking at infrastructure, human capital, governance and public-sector use cases. However, Nigeria still sits firmly in the middle-to-lower tier of African countries, reflecting the infrastructure and talent gaps noted above (Oxford Insights, 2023). Recent work has challenged technology-centric conceptions: Duan, Edwards and Dwivedi (2019) argue that organizational readiness for AI is fundamentally a social and managerial phenomenon – as much about leadership vision, culture and change capacity as about infrastructure – while Marda and Narayan (2020) advance a critical readiness framework centred on equity, power and contextual appropriateness, warning that mainstream frameworks systematically undervalue these concerns, with especially problematic consequences for the Global South. The critical lens is directly relevant in Nigeria where questions of who benefits from AI, how systems are governed and whose values are encoded are of pressing practical and ethical significance.

Organizational Flexibility and Dynamic Capabilities

Strategic management is fundamentally concerned with an organization's ability to reconfigure its resources, processes and strategies in response to changes in its environment. The dominant lens for explaining advantage in the face of rapid technological change is the Dynamic Capabilities framework first articulated by Teece, Pisano and Shuen (1997) and refined by Teece (2007, 2018). Dynamic capabilities differ from operational capabilities in that they are about change: sensing emerging opportunities and threats, seizing them through reconfiguring resources, and transforming existing competencies and business models as competitive conditions change (Teece, 2018).

This lens, when applied to AI, has attracted increasing attention. Holmström (2022) contends that AI changes the nature of dynamic capabilities by automating sensing, seizing and transforming

functions that previously relied on human judgment, thus enabling what he calls “algorithmic dynamic capabilities” — machine-led scanning, pattern recognition and adaptive decision-making at speeds beyond human cognition. This is powerful, but it raises the question of which organizations can actually develop these capabilities, and under what conditions. Phan and Wood (2020) go one step further by framing AI readiness as a higher-order dynamic capability: not just adopting tools, but constantly reconfiguring the organization's AI ecosystem as technology, competition and regulation change. Dynamic reading readiness is apt for Nigeria, where everything is changing fast and firms have to keep revising their strategies to remain competitive.

The relationship runs both ways. AI is improving the sensing, decision-making and agility that enable organizations to be adaptable, but adaptability is a prerequisite for successful adoption. Whereas companies with rigid hierarchies, risk-averse cultures, poor data governance and low change-management capacity struggle to integrate AI even when the infrastructure is in place (Fountaine, McCarthy & Saleh, 2019; Westerman, Bonnet & McAfee, 2019). Culture has been repeatedly shown to be a critical mediator, with organizations that value learning, experimentation and data-driven decisions reporting significantly higher success in adoption (Davenport & Bean, 2018; Ransbotham et al., 2017). Absorptive capacity is also important; it is the ability to recognize, assimilate and apply external knowledge (Cohen & Levinthal, 1990; Zahra & George, 2002). High absorptive capacity helps firms to identify suitable artificial intelligence (AI) technologies, integrate necessary know-how and translate this into operational and strategic gains. Prior technological investment, workforce education, density of knowledge networks and availability of external technical assistance affect absorptive capacity in Nigeria (Mukherjee, Malhotra & Liu, 2019).

AI Adoption in Developing Countries: A Critical Review

The literature on AI adoption in emerging markets is growing but underdeveloped in comparison to work on advanced economies. Four themes are clear for Nigeria. First, infrastructure deficits are regularly the most fundamental barrier (GSMA, 2022; World Economic Forum, 2020). The basics reliable power, high-speed broadband and affordable cloud are harder to access and more expensive in emerging markets. Nigeria's electricity shortfall is one of the most severe in the world: the grid supplies

approximately 4,000–5,000 MW against an estimated demand of 30,000–40,000 MW (Ogunleye, 2020). Using diesel generators or other backup to compensate sharply increases the effective cost of AI infrastructure, beyond the reach of all but the largest organizations (IEA, 2022; Ndulu, 2006).

Second, the scarcity of talent is a big constraint. The global competition for AI specialists, especially from large US and Chinese firms, poses a real threat of brain-drain as data scientists are attracted to higher-paying roles abroad (OECD, 2023; Ndubuisi & Otioma, 2021). In Nigeria the shortage is a reflection of too few AI-specific university programmes, weak integration of data science and machine learning into curricula, as well as connectivity gaps that limit access to online learning (Bankole & Mimbi, 2017; Okonkwo & Ade-Ibijola, 2021). Nevertheless, there is a burgeoning community of self-taught practitioners and a number of universities – University of Lagos, Covenant University and the African University of Science and Technology – have introduced AI and data-science programmes (Bright, 2022).

Third, institutional and regulatory conditions count (Asongu, Nnanna & Acha-Anyi, 2020; Meissner, Polt & Vonortas, 2017). Where regulation is ambiguous, inconsistent or negative to innovation, firms face greater investment risk; where governance is positive, with clear rules around data protection and active public investment, adoption rates and use-case sophistication increase (OECD, 2021; WEF, 2020). The National Digital Economy Policy and Strategy (NDEPS) 2020–2030 and the more recent draft National AI Policy in Nigeria are important steps toward an enabling environment, although implementation and enforcement gaps remain (NCC, 2022; Federal Ministry of Communications and Digital Economy, 2024).

Fourth, multinationals and international technology companies are channels for AI knowledge and practice (Cantwell & Mudambi, 2011; Kolk, Rivera-Santos & Rufin, 2018). Google (through Google for Africa), Microsoft (via its Africa Transformation Office), IBM and Mastercard have invested heavily in talent, the start-up ecosystem and research capacity in Nigeria. While such initiatives can speed up capability-building, they also raise questions about the terms of technology transfer, the governance of locally generated data and the extent to which foreign investment aligns with Nigerian developmental priorities (Carmody, 2017; Birhane, 2021).

Nigerian Business Environment Institutional Context

To have a rounded view of AI readiness in Nigeria, it must be situated within the broader institutional environment, which is characterized by a complex and often contradictory mix of formal and informal rules, norms and enforcement mechanisms (Kolk & Lenfant, 2015; Acquah, 2016). The formal environment has well-documented weaknesses that bear directly on AI strategy: an evolving but bureaucratically complex regulatory framework, inconsistent policy, and unpredictable enforcement (World Bank, 2023). Businesses most often cite compliance costs and policy uncertainty as barriers (PwC Nigeria, 2022) and the country is low on ease-of-doing-business measures. On data protection, a critical piece of AI governance, the framework was strengthened by the Nigeria Data Protection Regulation (2019) and the Nigeria Data Protection Act (2023), although enforcement capacity is still developing (NITDA, 2023).

The informal environment, with its strong relational networks, the importance of ethnic and regional ties, and a cultural emphasis on personal trust, can either facilitate or impede adoption (Nwachukwu et al., 2019; Okafor, 2021). Trusted networks can be diffusers of AI knowledge and accelerate learning in organizations; conversely, a preference for personal relationships over algorithmic mediation can drive AI resistance in credit assessment, HR and customer service. The macroeconomic backdrop adds further strain: over the review period Nigeria experienced two recessions (2016 and 2020), persistent currency depreciation, high inflation and sustained fiscal deficits (Nwafor, 2021; CBN, 2023). Foreign-exchange pressure raises adoption costs directly, as AI infrastructure and software licences are largely imported, even as margin pressure can, paradoxically, sharpen incentives for efficiency-seeking AI.

The financial sector is a key player, both in terms of early adoption and enabling investment across the economy. The Central Bank of Nigeria has been relatively progressive, creating a Regulatory Sandbox that allows institutions to test AI-driven products in a controlled environment (CBN, 2021). Among the most active adopters are the Tier-1 banks GTBank, Access Bank, Zenith Bank and First Bank which have deployed service chatbots, fraud detection, credit-risk models and process automation (EFInA, 2022; Deloitte Nigeria, 2023). A second locus of uptake is telecommunications, led by MTN, Airtel, Glo and 9mobile, with investment in network optimization, customer analytics and service

personalization (NCC, 2023). The wider digital economy e-commerce, payments, streaming, agritech is growing rapidly, creating ever larger datasets and competitive pressures that push adoption across the board.

Limitations of Existing Literature

The review reveals four gaps that this study addresses. The first is the dearth of theoretically integrated, empirically grounded analyses of organizational AI readiness in Nigeria; current work tends to be narrowly sectoral, more descriptive than analytical, or oblivious to the country's distinctive institutional dynamics. Second, the under-theorization of contextually adaptive AI readiness, which is the capacity to build AI capabilities that are appropriate and sustainable within a firm's particular institutional and resource environment; current frameworks implicitly assume convergence toward a single global standard. The third is the largely uncharted relationship between AI readiness and adaptability in post-digital emerging markets, where the enabling conditions may differ considerably from those in advanced economies. The fourth is the scant attention to policy implications for African markets, where most recommendations are based on advanced-economy evidence. The study contributes in all four theoretical, empirical and policy.

Theoretical Framework

The Dynamic Capabilities Theory

As its primary lens for the readiness–adaptability relationship, the study uses Dynamic Capabilities (Teece, Pisano & Shuen, 1997; Teece, 2007, 2018). The framework suggests that sustainable advantage in fast-changing environments is not achieved by holding valuable resources – the focus of the Resource-Based View – but by the ability to continuously sense, seize and reconfigure the resource base as the environment changes. Sensing capabilities enable firms to detect and evaluate external opportunities and threats, from technological and competitive moves to regulatory and customer change. Seizing capabilities commit resources to identified opportunities via investment, business-model and organizational-design decisions. Transforming (or reconfiguring) capabilities are the routines and leadership behaviours that keep the asset base, processes and structures in step with environmental demands (Teece, 2007).

It is illuminating to map AI onto these processes. Machine-learning-based predictive analytics, social-media monitoring and real-time market intelligence

transform the speed, scope and sophistication of environmental scanning for sensing. For seizing, AI provides faster, more effective responses through automation, personalization and intelligent decision support. For transformation, AI allows for truly new organizational forms, business models and strategies, not just incremental digital improvement. Yet the standard framework doesn't fully capture the constraints Nigerian firms face in building AI-enhanced capabilities: the cost of infrastructure relative to resources, the scarcity of talent, institutional barriers to experimentation, and thin knowledge networks for diffusing best practice. The study extends the framework by foregrounding these resource and institutional constraints and theorizing how firms can build capabilities that are effective and sustainable within them, the idea captured in contextually adaptive AI readiness.

Technology–Organization–Environment (TOE) Framework

The TOE framework (Tornatzky & Fleischer, 1990; Baker, 2012) provides a complementary lens on the multi-level determinants of adoption. It distinguishes three contexts: the technological (characteristics of available technologies and a firm's existing infrastructure), the organizational (size, managerial structure, human-resource endowments and culture) and the environmental (competitive landscape, regulation and the availability of suppliers and support). The framework has been widely used in developing countries (Kabanda & Brown, 2017; Usman & Oyefolahan, 2016) and empirical studies on cloud computing, mobile commerce, and ERP adoption in Sub-Saharan Africa have consistently found that environmental and organizational factors strongly moderate the relationship between technological availability and adoption (Tarhini, Elyas & Akour, 2016; Madukoma, Akpan-Obong & Popoola, 2014).

The framework reveals the interdependence of technological infrastructure (data quality, computing resources, API ecosystems), organizational characteristics (leadership vision, change-management capacity, talent development) and environmental conditions (competitive pressure, regulation, talent-market dynamics) in jointly shaping AI adoption trajectories and, therefore, AI readiness. Crucially it rejects the assumption that superior technology is adopted automatically and stresses instead that decisions are mediated by the full constellation of factors in which firms are embedded. That contextual sensitivity helps explain the differential unfolding of adoption across Nigerian

firms with similar technical capacity but different organizational and environmental configurations.

Theory of Institution

The third pillar is Institutional Theory (DiMaggio & Powell, 1983; Scott, 2014; North, 1990), which attends to the ways in which formal and informal rules, norms and cognitive frameworks shape behaviour. The work of DiMaggio and Powell on institutional isomorphism, the tendency of organizations within a field to become similar through coercive, mimetic and normative pressures, bears direct relevance to the adoption of AI in Nigeria. Coercive isomorphism stems from regulation and policy, such as when the CBN's Know-Your-Customer and Anti-Money-Laundering requirements drive banks to adopt AI-based compliance and fraud detection. Mimetic isomorphism comes out of uncertainty, seen in how smaller banks and telecoms copy the AI strategies of bigger, globally connected peers. Normative isomorphism propagates via education, consultancies, and professional associations that more and more influence professional communities related to AI.

A useful distinction between formal and informal institutions is made by North (1990). The formal environment for AI data-protection law, telecoms regulation, competition policy, AI strategy — is still nascent, creating ambiguity and risk. Just as important, but less systematically studied, is the informal environment: cultural norms around privacy, trust in algorithmic systems, and attitudes to data sharing. The study relies on both dimensions to provide a more complete account of the institutional determinants of readiness and adaptability.

Integrated Framework for AI Readiness and Adaptability

The integration of the three theories results in a multi-level, contextually grounded framework, based on five interrelated dimensions of contextually adaptive AI readiness.

- (1) Technological infrastructure readiness encompasses the quality and reliability of digital infrastructure (connectivity, power, and cloud access), the availability and governance of data assets, and cyber security posture corresponding to the TOE technological context and the resource base of dynamic capabilities.
- (2) Human capital and talent readiness relates to the availability, quality and retention of AI-competent personnel, the AI literacy of leadership, and the capacity of HR systems to attract and develop talent central to the seizing and transforming functions.

(3) Organizational culture and leadership readiness refers to the extent to which culture is conducive to experimentation, data-driven decisions, cross-functional collaboration and learning from failure, the credibility of leadership's AI vision, and change-management capacity key for sensing and transforming.

(4) Regulatory and institutional readiness refers to the clarity of the legal framework for AI and data, government support (incentives, grants, partnerships) and the density of the surrounding institutional ecosystem (research centres, professional associations, consortia, international partnerships) in line with the environmental context of the TOE and the institutional dimension.

(5) Strategic vision and AI-governance readiness captures how deeply AI is embedded in core strategy, the maturity of governance structures (ethics committees, algorithmic audit, AI risk management) and the clarity of data strategy the apex dimension that integrates the others into a coherent orientation toward AI-driven advantage.

Contextually adaptive AI readiness is therefore the extent to which an organization has assembled a configuration of these five dimensions that is not only technically advanced but also institutionally appropriate, resource-realistic and strategically sustainable within its specific environment. The construct explicitly denies that readiness is a one-dimensional, universally calibrated property, acknowledging that firms in different institutional settings may achieve high adaptability through different combinations of readiness dimensions with direct implications for how readiness should be assessed in Nigeria and beyond.

Methods

The study adopted an interpretive, qualitative-dominant mixed-methods design grounded in critical realism and constructivism to examine AI readiness in Nigeria. Data were collected through semi-structured interviews, organizational document analysis, and secondary quantitative sources. Primary data comprised 42 key informant interviews with industry leaders, AI practitioners, regulators, and experts across the financial services, telecommunications, FMCG, public, and technology sectors, selected through purposive and snowball sampling. Organizational documents from 24 major AI-related organizations were systematically analysed, while secondary data were obtained from national and international reports, including publications from regulatory agencies and development organizations.

Qualitative data were analysed thematically using NVivo, while quantitative data were analysed using descriptive statistics, trend analysis, and cross-tabulations with SPSS and Excel. Triangulation and member checking enhanced the credibility of findings. Validity was ensured through theoretical grounding, multiple data sources, and rich contextual descriptions, while reliability was supported by maintaining an audit trail and systematic coding procedures. Ethical standards were upheld through informed consent, confidentiality, anonymization of data, and approval from the institutional research ethics committee.

Findings and Discussions

The AI Infrastructure Landscape in Nigeria

The analysis starts with the technological conditions that create the enabling environment for AI. Evidence of large infrastructure gaps is evident but pockets of recent progress raise cautious optimism. Internet connectivity, the most basic requirement for cloud-based AI, has grown markedly. Active subscriptions reached roughly 154 million by end-2023, about 70% mobile-broadband penetration (NCC, 2023). But quality and reliability vary greatly, with a distinct rural-urban divide and a gulf between large enterprises on dedicated fibre and the SMEs and individuals reliant on congested mobile networks (Ookla, 2024). Average fixed-broadband download speeds of about 12 Mbps in early 2024 are behind comparators such as South Africa (about 29 Mbps) and don't provide the bandwidth that some advanced AI applications need.

The hyperscalers are expanding cloud infrastructure. Microsoft Azure, AWS and Google Cloud have set up or announced nodes in Nigeria or neighboring South African facilities, with direct impacts on latency, sovereignty and cost (Deloitte, 2023). Local data centers like MainOne (now Meta-owned), Rack Centre and Medallion Communications in Lagos

have improved provision, but costs are still far in excess of advanced-economy levels and interviewees in banking and telecoms pointed to cloud costs as a key constraint on the scale of investment.

“The infrastructure is getting better but it's still very costly compared to our revenue. If you add in the costs of data egress, currency conversion and bandwidth, then running our machine-learning models on AWS costs three to four times what the equivalent institution in the UK pays. “That limits the commercial viability of AI at scale.” — Chief Data Officer, Tier-1 Commercial Bank, Lagos

The power deficit, which has long been identified as a major constraint to ICT infrastructure, became an important hidden cost for all the sectors. All sampled organisations reported significant spending on diesel generators, solar installations or UPS systems to keep data-centre and computing operations running, with several estimating that electricity accounted for 20-35% of their total ICT infrastructure budget – resources that could otherwise fund AI capability.

Data infrastructure differs widely across sectors. The financial services sector is relatively rich in data – transaction records, credit histories, logs of digital interactions – but the quality of that data is often poor, with missing records, data held in isolated systems and weak cleaning. Telecoms has huge amounts of data on calls, network traffic and device use, but localization rules and sovereignty concerns restrict its use. In FMCG, fragmented distribution, low levels of digitization at point-of-sale, and the dominance of informal retail hinder data completeness, limiting demand forecasting and supply-chain optimization. The public sector collects vast quantities of administrative data but is plagued by quality issues, non-interoperable systems and almost non-existent data-governance frameworks.

Table 1. Dimensions of AI infrastructure readiness across Nigerian sectors

Dimension	Financial Svcs	Telecoms	FMCG	Public Sector	Score*
Broadband quality	High (fiber)	High (own net)	Medium	Low–Medium	3.0/5
Data asset quality	Medium–High	High	Low–Medium	Low	2.5/5
Cloud adoption	Medium	Medium–High	Low–Medium	Very Low	2.3/5
Power reliability	Medium (backup)	Medium–High	Low–Medium	Low	2.2/5
Data governance	Medium (CBN)	Medium	Low	Very Low	2.0/5
Cybersecurity posture	Medium–High	Medium	Low–Medium	Low	2.4/5

*Composite qualitative assessment (1 = Very Low, 5 = Very High). Author's fieldwork synthesis, 2024–2025.

Profiles of AI readiness by sector

Readiness and adoption are very differentiated across sectors influenced by the interplay of infrastructure endowments, competitive dynamics, regulatory pressure and organizational capability.

Finance Services

The highest overall readiness is in financial services, driven by competitive pressure from fintech disruptors, regulatory mandates rewarding data-driven compliance and relatively rich data. The most sophisticated applications in banking can be grouped into four categories: customer-service automation (chatbots and virtual assistants – notable examples include Zenith Bank's ZiVA and Access Bank's Tamada), fraud detection and AML compliance (transaction monitoring via machine learning), credit scoring (combining bureau data with alternative indicators such as mobile-money histories) and process automation via RPA. Deployment is patchy even here: most applications are customer-facing and analytically simpler chatbots, FAQ automation, rule-based fraud detection rather than complex credit-risk modelling, portfolio optimization or strategic market intelligence. They blamed data-quality constraints, under-investment in R&D and a risk-averse culture that favors proven applications over experimentation.

"We have made significant progress in utilizing AI for KYC onboarding and transaction monitoring, partly due to CBN requirements, which created a clear business case. But we are still early with AI for strategic decision-making, portfolio allocation or truly transformative model innovation. The biggest challenge is the talent pipeline." — Head of Digital Transformation, Tier-2 Commercial Bank, Lagos

The fintech sub-sector is more volatile. Paystack, owned by Stripe, Kuda, Cowrywise and Renmoney have all built AI-first operating models that leverage mobile data, transaction histories and behavioral signals to deliver personalized products at scale. They benefit from international capital and expertise that creates a talent and knowledge premium unavailable to traditional banks.

Telecommunication

Telecom is a mix of data richness, technical depth and fierce competition between four operators. Applications include network operations (traffic prediction, capacity planning), customer experience (churn modelling, personalized offers, AI-assisted care), fraud management (SIM-swap detection, revenue assurance) and value-added-service personalization. MTN Nigeria, the market leader with about 75 million subscribers in 2023, has the biggest reported investments like a network-operations center with ML-based predictive maintenance and a

sophisticated customer-analytics platform; Airtel Nigeria uses global capabilities of parent Bharti Airtel for analytics and optimization. Constraints remain formidable. The NCC's data-localization requirements cause friction with cloud-based deployment and increase compliance costs. A shortage of AI-savvy network engineers impedes embedding into core operations. And naira depreciation drives up the cost of imported equipment and software, squeezing investment budgets.

Fast Moving Consumer Goods (FMCG)

FMCG is the most mixed sector, with multinationals' subsidiaries (Nestlé Nigeria, Unilever Nigeria, PZ Cussons, Nigerian Breweries) and large local conglomerates (Dangote Group, Dufil Prima Foods, Chi Limited). Subsidiaries tend to be better prepared, adopting practices, tools and governance from their parents, as well as accessing global talent and higher levels of supply-chain digitization – but even they find it hard to adapt global frameworks to Nigerian conditions, especially in terms of point-of-sale data capture (limited by informal retail), connectivity and local skills. Local firms are even further behind: most are at a basic stage of transformation — ERP implementation, digitized order management, basic business intelligence with AI confined to isolated pilots in demand forecasting or distributor analytics, and usually dependent on external consultants, not in-house capability.

Public Sector

Overall, the public sector is the least prepared, which is in line with the international literature on public-sector AI in developing countries (Androutsopoulou et al., 2019; Misuraca & van Noordt, 2020). Disjointed pilots, weak coordination, poor data infrastructure, acute talent shortages and a governance environment ill-suited to the experimentation and agile implementation AI requires are all hampering adoption. But there are exceptions. The Federal Inland Revenue Service has employed AI-supported tax-compliance and audit-targeting; the Corporate Affairs Commission has automated portions of business registration; and the National Health Insurance Scheme has piloted claims-fraud detection. But these efforts are piecemeal and run into funding, retention and change management difficulties. The Renewed Hope Agenda of the current administration and the work of the Federal Ministry on a National AI Strategy could improve the enabling environment in the medium term (Federal Ministry of Communications and Digital Economy, 2024).

However, translating policy into operational capability will require sustained investment, institutional reform and a major upgrade of public-sector technical human capital.

AI Capability Gaps and Human Capital.

Human capital is the most salient dimension across all sectors and types of organisation – the availability, quality and retention of AI-competent talent was the single most-cited constraint. Demand is growing quickly, with financial services, telecoms and start-ups and increasingly public agencies and FMCG companies improving their digital capability. According to LinkedIn data, the number of postings that require data science, machine learning, and AI engineering skills have almost doubled between 2020 and 2023. The average time-to-hire for senior AI roles has stretched to four to six months amid heightened competition (LinkedIn, 2023).

On the supply side, universities are gradually increasing the number of programmes, but growth is slower than demand, and quality is variable. The most binding constraints on supply are limited lab computing infrastructure, curricula that fail to keep up with the rate of technological change, inadequate industry-relevant practical experience, and a small pool of experienced practitioners, largely based in Lagos, who can mentor and teach. Outside the concentration in Lagos, firms are at a distinct disadvantage when competing for scarce talent. The brain drain compounds the problem: many participants reported that trained staff left for opportunities in the United States, Canada and the United Kingdom within 12–24 months, lured by higher pay, career prospects and quality-of-life issues.

“We hire and train young data scientists every year and a large percentage of them leave within two years. The pull factors are strong, a good Nigerian data scientist can triple their compensation joining a UK or US firm, even remotely. “We are fighting powerful structural forces with retention packages, flexible working and interesting projects but we are fighting powerful structural forces.” — Chief People Officer, Fintech Company, Lagos

In the analysis, three levels of talent are identified. Tier-1 talent (highly skilled data scientists and ML engineers that can build and deploy advanced systems) is in very short supply, concentrated in a handful of organizations, and very exposed to emigration. Tier-2 talent – analysts who have data and basic-ML skills and can run tools built by others – is more available but still short of demand, particularly outside of Lagos. Tier-3 talent – business

and operational staff who are sufficiently AI-literate to understand and act on AI outputs – is the most broadly in demand and the most amenable to in-

house training, but investment in developing it is still badly underfunded.

Table 2. Sectoral demand–supply gap in AI human-capital readiness

Indicator (1–5)	Financial Svcs	Telecoms	FMCG	Public Sector
AI talent demand intensity	4.5	4.2	2.8	2.5
AI talent supply adequacy	2.1	2.4	1.8	1.3
Leadership AI literacy	3.2	3.5	2.2	1.9
Availability of staff AI training	3.0	2.8	1.9	1.4
Talent-retention challenge	4.1	3.8	3.2	2.5
Composite HC readiness	2.8/5	3.0/5	2.1/5	1.7/5

Scores are researcher judgments from qualitative analysis. Author's fieldwork, 2024–2025.

Organizational Culture and AI Adaptability

Culture is a crucial mediator, often more decisive than infrastructure or even talent. The study, consistent with the broader literature (Davenport & Bean, 2018; Fountaine, McCarthy & Saleh, 2019), identifies five culturally salient dimensions in the Nigerian context: data-drivenness (decisions based on analysis rather than intuition or hierarchy); psychological safety for experimentation (employees feeling safe to propose AI ideas and accept project failures); cross-functional collaboration (integrating technical and business expertise rather than confining AI to IT); learning orientation (systematically capturing and applying lessons from AI successes and failures); and leadership AI ambidexterity (managing existing operations while pursuing exploratory capability-building).

Companies that score highly on these dimensions are much better at translating AI investment into advantage. The most successful adopters share several characteristics: strong chief-data-officer-equivalent roles with direct access to executives; cross-functional AI teams that bring together data scientists, domain experts and strategists; explicit tolerance for experimental failure with structured post-project learning; and attention to data literacy at every level, including the board.

“The technology is the easy part. We can bring in consultants to build models. What we can’t outsource is the cultural change: getting relationship managers to actually use the AI credit

recommendations, getting branch managers to trust data over gut instinct. That’s the slow, hard work of making sure AI delivers value here.” — Group Managing Director/CEO, Commercial Bank, Abuja

The study also stresses the importance of culture in resisting radical change, citing fears of job displacement (especially among lower and middle managers whose work involves data processing), suspicion of opaque decision logic, a desire for personal relationships over algorithmic mediation, and a norm of deference to authority that can inhibit the grass-roots experimentation that AI requires. Another factor is ownership. Multinational subsidiaries have stronger cultural foundations in governance and psychological safety, supported by the parent company, but their global AI cultures are not always well adapted to Nigeria – several participants spoke of tensions between global governance frameworks and local data practices, client preferences and ethical norms that required careful mediation.

Policy Framework and Regulatory Setting

Dramatic changes in the regulatory environment have occurred during the review period. Absent in 2015, by 2026 it had developed into an emerging architecture of data protection, digital-economy regulation and nascent AI-specific policy. The most consequential development is the Nigeria Data Protection Act (NDPA) of June 2023 which replaced the 2019 Regulation and established the Nigeria Data Protection Commission as statutory regulator.

Some NDPA provisions directly apply to AI, including mandatory processing agreements between controllers and third-party AI providers; restrictions on automated decision-making with significant effects on individuals, including a right to human review; data-minimization requirements limiting collection for training; and localization provisions affecting offshore cloud AI (NDPA, 2023; Akinwale & Adesanya, 2023).

The CBN's fintech framework is especially relevant to financial-services readiness. Its Regulatory Sandbox, since 2021, has provided fintechs with a structured route to market, enabling them to test AI-based products – alternative credit scoring, AI-driven savings – under supervision. But approval is a long and uncertain process for new applications, and the CBN's conservative stance on AI in core banking (due to model-risk and bias concerns) has delayed adoption in credit-risk modelling and algorithmic trading. At the strategy level, NDEPS 2020–2030 identifies AI as a priority under its Digital Economy Enablers pillar, and the draft National AI Policy – developed by the National Centre for Artificial Intelligence and Robotics (NCAIR) under NITDA – signals growing government awareness, committing to investment in talent, research infrastructure, ethical governance and adoption in priority sectors (NITDA, 2023; Federal Ministry of Communications and Digital Economy, 2024).

But this progress is constrained by four gaps in readiness. The first is a coordination deficit across the many agencies with AI interest – NITDA, NCC, CBN, SEC and sector regulators. This creates a fragmented, sometimes contradictory environment that incurs compliance costs and uncertainty. Second, the NDPA's enforcement capacity is still nascent, so the practical implications for artificial intelligence systems are unclear. Third, public investment in AI research and public sector capability is still far from matching the challenge, and public-private knowledge transfer mechanisms are underdeveloped.

Fourth, Nigeria does not have a coherent competition-policy framework that addresses the market-power implications of the AI-driven concentration of data that is beginning to place the largest, most data-rich firms at an advantage over smaller players.

Taxonomy of Nigerian Organizational AI Readiness

Combining the results across the five dimensions results in an empirically based taxonomy of four archetypes of readiness. AI Vanguarders are a small group of big, internationally connected organizations mostly Tier-1 banks, leading fintechs and the bigger telecoms that have invested heavily and consistently across dimensions. They have a relatively strong infrastructure, growing talent pools, active governance and clear strategic integration, use AI across multiple functions, realize measurable returns and increasingly build proprietary capability. A larger group, AI Aspirants, made up of Tier-2 banks, mid-sized telecoms, larger FMCG multinationals and some agencies, see AI's strategic importance and are investing, but whose maturity is hindered by talent, infrastructure or cultural shortfalls. They are characterized by a gap between strategic intent and operational capability and a tendency toward incremental, siloed pilots.

AI Experimenters include medium-to-large local FMCG firms, mid-sized financial institutions, and some state agencies, experimenting in isolated, exploratory ways (usually vendor tools or consultancy projects) without the strategic commitment, internal capability, or culture to scale. They experience “AI pilot purgatory,” where proofs of concept prove feasibility but never go into production. AI Abstainers – predominantly SMEs from across sectors, many public agencies and a lot of local firms in traditional sectors – have not yet really started to engage, due to limits on resources, gaps in awareness, culture or a feeling that AI is irrelevant to their model. But they also represent the largest potential market for accessible, affordable, contextually appropriate AI. They face the greatest long-term competitive threat from more AI-ready peers.

Table 3. Taxonomy of Nigerian organizational AI-readiness archetypes

Dimension	AI Vanguard	AI Aspirant	AI Experimenter	AI Abstainer
Typical org type	Tier-1 banks, fintechs, top telecoms	Tier-2 banks, MNC FMCG, mid telecoms	Mid local firms, some agencies	SMEs, most govt, traditional sectors
Infrastructure	Medium–High	Medium	Low–Medium	Low–Very Low
AI talent	Medium (gaps)	Low–Medium	Low (vendor-dep.)	Very Low
AI culture	Medium–High	Medium	Low	Very Low
AI strategy	Explicit, board-level	Functional only	Opportunistic/ad hoc	Not present
Key AI risk	Talent attrition, ethics gaps	Pilot purgatory, talent gap	Low ROI on projects	Competitive displacement

Synthesis of author's fieldwork, 2024–2025.

Discussion

Implications for Theory

Dynamic Capabilities in Resource-Constrained Contexts

In their original formulations (Teece, Pisano & Shuen, 1997; Teece, 2007, 2018), dynamic capabilities are theorized in relatively well-resourced settings where the main barriers to capability development are cognitive and strategic rather than infrastructural and institutional. The Nigerian evidence challenges this assumption and makes the case for a contextual extension that considers the resource and institutional factors that mediate the relationship between AI investment and adaptability. AI-enabled capabilities, especially in resource-poor environments, develop along a different trajectory than the additive, incremental model in the mainstream literature. The most ready firms (AI Vanguard) achieved high adaptability not by sequentially building all five readiness dimensions to a high level, but by focusing resources on those dimensions most critical to their competitive context and developing compensating strategies for those dimensions constrained by structural factors.

This supports and qualifies Phan and Wood's (2020) view of AI readiness as a higher-order dynamic capability: in constrained environments, it is the meta-capability of contextually adaptive AI readiness configuring capabilities optimally given

environmental and resource limits that matters more than the absolute level of investment in any single dimension. The extension goes beyond Nigeria to other emerging markets, resource-constrained public agencies and SMEs in advanced economies. Moreover, the study identifies a unique dimension of adaptive AI sensing: firms with strong networks for AI monitoring and understanding among their international peers through multinational collaborators, consultants, and diaspora professionals exhibit superior sensing capabilities that compensate for inadequate internal R&D. This is in line with Mowery and Nelson's (1999) work on international knowledge transfer as a source of innovative capacity in late developing economies and suggests that network embeddedness is a readiness dimension in its own right.

Mediation by Institutions and a Contextual Theory of Readiness

The evidence indicates that AI readiness is not merely technological or organizational but institutionally structurally mediated. The adoption patterns in Nigeria cannot be explained by infrastructure or resources alone. They depend on the interplay of formal regulation, informal cultural norms, talent-market dynamics and the political economy of the digital sector in determining when readiness can arise and be mobilized for benefit. This extends the institutional view of adoption (DiMaggio & Powell, 1983; North, 1990; Scott, 2014)

in three ways. It begins with the observation that institutional pressures are unevenly distributed: coercive pressures (regulatory mandates) are most salient for large regulated firms; mimetic pressures are more relevant for Aspirants and Experimenters who want to reduce uncertainty; and normative pressures are dominant in the fintech and start-up ecosystem where professional norms and international investment standards set the tone for practice.

Second, it recognizes institutional AI leapfrogging, the capacity to leapfrog the sequential capability-building route of advanced-economy firms and move straight to the adoption of sophisticated tools through international partnerships, diaspora networks and technology transfer. Similar to leapfrogging in African telecoms, this offers real acceleration, but also introduces specific risks, such as the gaps between adopted technological sophistication, and inhouse maintenance and governance capability. Third, it offers the construct of institutional AI readiness, separate from organizational readiness: the extent to which the wider environment – regulation, talent ecosystem, knowledge infrastructure and digital political economy – enables rather than constrains organizational AI development. This systemic construct is poorly represented in current frameworks, yet it is central to understanding national-level drivers and designing interventions that address the institutional underpinnings of readiness.

Formalizing AI Preparedness for Contextual Adaptation

The main contribution of this research is the construct of contextually adaptive AI readiness, which is proposed in the framework and empirically supported. It captures the insight that readiness in constrained environments is not a scaled down version of advanced-economy readiness but qualitatively different in configuration, developmental trajectory and relationship to adaptability. Formally, it is the capacity for an organization to build and implement a configuration of AI capabilities that (a) creates relevant competitive or operational value within the organization's institutional and resource environment; (b) is viable under its financial and human-capital limitations; (c) reacts dynamically to changes in the AI landscape and sector competition; and (d) is integrated into processes, structures, and cultures that foster ongoing learning. Focusing on contextual sustainability and dynamic adaptiveness rather than absolute capability levels makes the

construct more relevant and theoretically coherent for emerging markets.

Three practices distinguish firms with high contextually adaptive readiness, whether Vanguards or Aspirants: they have systematic processes for assessing AI opportunities against their specific constraints; they create hybrid capability models that combine modest in-house expertise with strategic external partnerships rather than duplicating fully internalized advanced-economy stacks; and they invest more heavily in culture and leadership AI literacy than in technology alone, realizing that cultural and leadership readiness is the most difficult dimension to replicate in the Nigerian context.

Practical and Managerial Implications

The first step is for leaders to craft a contextually appropriate AI strategy rather than import playbooks from advanced economies. Companies that understand the most valuable use cases in Nigeria, looking at local demand patterns, data landscapes and competitive dynamics, achieve higher returns. This will involve building in-house strategic intelligence on the Nigerian AI landscape, with constant engagement across the regulatory environment, talent ecosystem and sector competition. Second, as culture and talent are the most binding constraints, investment should be re-balanced towards them. Firms that over-invest in infrastructure and under-invest in talent, leadership literacy and culture systematically under-perform. There is evidence of structured AI leadership development, data literacy programmes for non-technical staff, cross-functional AI teams and explicit culture initiatives that foster psychological safety for experimentation and learning from failure.

Thirdly, the archetype taxonomy offers a diagnostic tool to organizations to locate themselves, to understand the archetype-specific risks and to design targeted development strategies. Aspirants more than anyone need clear plans for how to get out of pilot purgatory by putting in place the change management, data governance and talent foundations to scale pilots into production. Fourth, international AI partnerships are strategically important, particularly for Aspirants and Experimenters partnerships with multinationals, international research bodies and diaspora networks can provide know-how, resources and talent that would be prohibitively expensive to build on one's own. Firms must manage the conditions of such partnerships so that they build real internal capability rather than remain perpetually dependent on outside

providers, a dependency that would constrain long-term adaptability and competitive autonomy.

Policy Implications

First, the evidence points to a coherent national AI-infrastructure strategy that tackles the electricity, connectivity and cloud deficits identified as fundamental barriers. The magnitude of the deficit – especially for power and broadband outside of major cities – exceeds the capacity of the private sector and calls for continued public investment and strategic alliances. Specific measures include prioritising renewable energy infrastructure in line with Nigeria's climate commitments, expanding the National Broadband Plan with more fibre-backbone investment and negotiating favourable cloud agreements with hyperscalers to reduce costs for local organisations.

Second, the talent shortage requires a sustained increase in public investment in AI education and research: AI Centres of Excellence at five or more geographically dispersed universities with the required computing infrastructure and international faculty partnerships for world-class research and teaching; mandatory AI and data-science modules in all university STEM programmes; a national AI scholarship and fellowship scheme to develop talent and address brain drain; and a structured returnee programme with incentives to diaspora professionals to contribute to the national ecosystem. Third, the regulatory environment requires coordinated reform to reduce fragmentation, uncertainty and compliance costs: a multi-agency AI Regulatory Coordination Council chaired by the Minister for Communications and Digital Economy; fast-tracked, proportionate operationalisation of the NDPA's AI-specific provisions that does not stifle innovation; extension of the CBN Sandbox to AI applications beyond financial services; and a government AI-procurement strategy that uses public demand to stimulate market development and local capability.

Fourth, the study proposes a National AI Readiness Assessment Framework adapted from international models but extended to the institutional and structural dimensions identified here to support periodic sector- and organization-level assessments, build the evidence base for specific measures, and allow firms to benchmark against peers and national targets. Fifth, in line with the construct of institutional AI readiness, policy should take an ecosystem approach that encompasses not just individual organizations but the systemic conditions of readiness: knowledge infrastructure (research centres, data commons, standards bodies), social

infrastructure (AI-ethics communities, professional associations, industry consortia) and international connectivity (bilateral research partnerships, development-bank programmes, diaspora-engagement platforms) that together constitute the institutional basis of organizational AI readiness.

Conclusion

The study analyzed the relationship between AI readiness and organizational adaptability in the post-digital economy of Nigeria. The study provides a theoretically integrated, empirically grounded, and practically actionable analysis of a rising and important phenomenon. It has demonstrated that AI readiness in Nigeria is complex, multi-dimensional and institutionally mediated – not sufficiently depicted by the technology-centric, advanced-economy paradigms that dominate the literature. The integrated framework combining Dynamic Capabilities Theory, the TOE framework and Institutional Theory presents a multi-level architecture for understanding the technological, organizational, cultural, regulatory and strategic dimensions of readiness in all their complex interrelatedness. This contextually adaptive AI readiness concept, developed through the interplay of theory and evidence, is a distinctive and practically significant contribution. It speaks not only to Nigeria but also to the wider challenge of building AI-enabled capacity in resource-constrained, institutionally complex environments.

In practice, Nigeria is more developed than international assessments would indicate, but less developed than the ambitions of its leaders and policymakers would suggest. The financial services and telecommunications sectors have developed a body of practical experience that could underpin more advanced capability in the medium term. "There are big untapped opportunities in AI-enabled supply-chain and commercial transformation in the FMCG industry, but this will take a systematic approach to building data infrastructure and talent. The public sector is the least developed but most potentially high-leverage domain, given the scale of public-service delivery and the potential of AI in health, education, agriculture and administration. The four-archetype taxonomy—Vanguards, Aspirants, Experimenters, and Abstainers—offers a practical diagnostic of position, archetype-specific risks, and targeted strategies, and the recommendations on strategy, talent, culture, regulation, infrastructure, and ecosystem development are calibrated to the Nigerian institutional context.

A few limitations should be acknowledged. The qualitative dominant design is appropriate for the research questions but limits statistical generalizability and the data are focused on the formal private sector in large urban centres, leaving readiness in smaller cities, rural areas and the informal sector – a substantial share of activity only partially captured. Future research should extend into these areas. The rapid rate of change in AI means that particular findings about current adoption or specific tools should be interpreted with the understanding that developments may have occurred since data collection. The theoretical and taxonomic contributions are intended to be more enduring.

How Nigeria progresses on AI readiness and adaptability will depend on the speed and scale of public investment in infrastructure and education, the ability of regulation to evolve in ways that encourage rather than stifle innovation, the effectiveness of international partnerships in building capability without creating dependency, and the extent to which organizations cultivate the leadership literacy and cultures needed to convert investment into advantage. The study's most basic finding is that the future of AI in Nigeria will depend less on the sophistication of available technologies than on the quality of the human, organizational and institutional foundations on which they are deployed. Nigeria is at a historic crossroads. The post-digital economy offers real opportunities for AI-enabled leapfrogging that could accelerate transformation, create good jobs and widen access to essential services for 220 million people. Realizing that potential will require sustained, strategically smart action by leaders, policymakers and development partners — the kind of contextually grounded, evidence-based action that this study has sought to inform.

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