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Artificial Intelligence Adoption and Organizational Performance in Nigerian SMEs: Between Digital Promise and Structural Constraint

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Abstract: *Small and medium enterprises account for close to half of Nigeria's GDP and the overwhelming majority of its employment, yet the sector remains structurally fragile, undercapitalised, and technologically uneven. This paper examines the relationship between artificial intelligence adoption and organizational performance among Nigerian SMEs, situating the discussion within the wider debate on digital transformation in resource-constrained economies. Rather than treating AI adoption as a linear driver of efficiency, the paper argues that its performance effects in Nigeria are conditional, filtered through infrastructural deficits, managerial capacity, and an institutional environment that has not caught up with the pace of technological diffusion. Drawing on a qualitative synthesis of recent Nigerian and comparative African studies, alongside secondary data from SMEDAN, the National Bureau of Statistics, and the Nigerian Communications Commission, the paper applies the Technology-Organization-Environment framework and the Resource-Based View to interpret why AI adoption produces measurable gains for some firms and negligible or even counterproductive outcomes for others. The findings suggest that awareness of AI tools among Nigerian SME operators is high and rising, but actual integration remains shallow, concentrated in customer-facing functions such as chatbots and social media analytics, while deeper applications in inventory optimisation, credit scoring, and production planning remain rare. The paper contends that the dominant policy narrative, which frames AI as a leapfrogging opportunity, understates the extent to which existing infrastructural and financing gaps reproduce old inequalities in new technological form. It closes by arguing for a more differentiated policy approach that distinguishes between adoption as symbolic participation and adoption as operational transformation.*

Keywords: artificial intelligence, SME performance, digital transformation, technology adoption, Nigeria

Introduction

There is a particular kind of optimism that attaches itself to discussions of artificial intelligence in Africa, one that tends to arrive dressed in the language of leapfrogging. The argument, familiar from earlier waves of mobile telephony and mobile money research, runs roughly as follows: because African economies never built out expensive legacy infrastructure, they are unusually well positioned to skip directly to frontier technologies and capture productivity gains that took decades to accrue elsewhere. Artificial intelligence has become the latest bearer of this narrative, and Nigeria, as the continent's largest economy and most populous digital market, sits near the centre of it.

The empirical picture is less tidy than the narrative suggests. Nigeria's micro, small, and medium enterprises, which the National Bureau of Statistics and the Small and Medium Enterprises Development Agency of Nigeria (SMEDAN) place at over 39 million in number, contributing something in the region of 46 percent of GDP and close to 88 percent of employment (SMEDAN & NBS, 2021), operate under conditions that make any simple adoption-to-performance story hard to sustain. Power supply is unreliable. Broadband penetration, while it has grown, remains uneven across states and between urban and rural areas (Nigerian Communications Commission, 2023). Digital literacy is unevenly distributed even among firm owners who are otherwise commercially astute. And the financing architecture that would allow a small firm to invest in AI-enabled tools, rather than merely experiment with free or freemium versions of consumer-facing chatbots, is thin.

This paper takes as its starting point a discomfort with two positions that dominate the existing literature. The first, often found in consultancy reports and some of the more promotional academic writing, treats AI adoption as an unambiguous performance lever, citing global productivity figures from McKinsey or PwC as though they translate directly into the Nigerian SME context (Chui et al., 2023). The second, less common but increasingly visible in critical development studies, treats AI in Africa primarily as a vector of exclusion, in which the technology simply widens the gap between well-resourced firms and everyone else. Both positions contain a partial truth, but neither captures what is actually observable in the Nigerian data: a landscape of highly differentiated adoption, in which the same technology produces divergent outcomes depending on firm size, sectoral positioning, ownership structure, and the surrounding institutional environment.

The central argument advanced here is that AI adoption and organizational performance in Nigerian SMEs are connected by a relationship that is conditional rather than direct. Adoption without complementary organizational capacity, adequate infrastructure, and a minimum threshold of digital literacy tends to produce cosmetic or short-lived gains, if it produces gains at all. Where those conditions are met, even partially, the performance effects appear more durable, concentrated particularly in customer relationship management, marketing precision, and, to a lesser extent, inventory control. This is not a novel theoretical claim in the abstract; TOE-based studies in other emerging markets have made similar arguments (Soomro et al., 2025). What this paper adds is a Nigeria-specific interrogation of why the moderating conditions themselves are so unevenly distributed, and what that unevenness implies for the policy discourse around digital transformation in West Africa.

The paper proceeds as follows. Section two reviews the literature on AI adoption and SME performance, with particular attention to the Nigerian and broader West African evidence base and the methodological limitations that recur across that evidence. Section three sets out the theoretical framework, combining TOE with the Resource-Based View and offering a modest critique of both as applied to the Nigerian case. Section four explains the methodology, a qualitative thematic synthesis of published empirical studies and policy documents rather than primary survey data. Section five presents the findings, organised around the recurring themes that emerge from the synthesis. Section six develops the analytical argument in more depth, and section seven concludes with implications for research and policy.

Literature Review

The literature on AI adoption in African SMEs has grown quickly over the past three years, though much of it remains descriptive rather than explanatory, and a good deal of it originates from unpublished theses, conference proceedings, and journals with limited indexing. This is worth noting not as a dismissal but as a methodological caution: the evidence base is real and useful, but it is also uneven in quality, and this paper treats it accordingly.

Global and comparative evidence

Much of the initial framing for African AI adoption research borrows heavily from global consultancy data. Chui et al. (2023), writing for McKinsey, reported productivity increases linked to AI adoption when paired with strong management support, a figure that has since been cited almost reflexively across Nigerian studies as evidence of AI's transformative potential. The problem is not that the McKinsey figure is wrong; it is that it describes a population of firms, largely in advanced economies, with access to capital, technical staff, and stable digital infrastructure that bears only a loose resemblance to the median Nigerian SME. Citing it as a benchmark risks importing an implicit assumption that Nigerian firms are simply earlier on the same curve, when the more defensible reading is that many of them are on a different curve altogether, shaped by different constraints.

Comparative work from other emerging markets offers a more useful anchor. Studies of Indian SMEs have documented revenue gains linked to improved customer insight following AI adoption (Chui et al., 2023), while a 2020 empirical survey of German SMEs found that only 5.8 percent of firms sampled had actually applied AI in their operations, with most preferring long-established rule-based systems over genuinely adaptive tools (Ulrich et al., 2021). This gap between stated interest and operational use recurs consistently enough across contexts to be treated as close to a stylised fact rather than a peculiarity of one market. Muzuva et al. (2024) found a broadly similar pattern in South African SMEs, where enthusiasm for generative AI outpaced technical capacity to deploy it, constrained above all by limited technical knowledge and cost, even though a meaningful minority of adopters in their qualitative sample reported productivity gains once tools were embedded in daily operations. Ghana presents a partial counterpoint: Abrokwah-Larbi and Awuku-Larbi (2024), surveying 225 SMEs registered with the Ghana Enterprise Agency, found that AI use in marketing had a significant positive effect on financial, customer, internal process, and learning-and-growth performance, results that sit uneasily alongside the more constrained picture from Nigeria and South Africa and point toward country- and sector-level institutional differences as the more relevant unit of explanation than any general claim about "African SMEs" as a single population.

Nigeria-specific evidence

Within Nigeria, the empirical base has diversified geographically, though it remains concentrated in the southern states, with comparatively little published work from the North. Adegbuyi et al. (2024), surveying 355 SME operators across Southwest Nigeria, found that 75 percent of respondents reported awareness of AI technologies, but only 55 to 63 percent claimed to understand their industry-specific applications, and actual adoption trailed both figures considerably. The barriers they identified, financial constraints, inadequate technological infrastructure, insufficient technical manpower skills, and a degree of cultural and organizational resistance, are echoed closely by a separate Southwest Nigeria study using structural equation modelling on 220 SME respondents, which found that perceived AI complexity actively suppressed both employee capability and management support, while management support itself remained the strongest positive predictor of firm performance (Akinruwa et al., 2025). That two independently conducted studies in the same broad region converge on a similar barrier structure is itself notable; it suggests these are not idiosyncratic local frictions but a more durable structural pattern.

Arachie et al. (2025), examining Southeastern Nigeria and building on an earlier conceptual study of AI as a sustainability catalyst for the same SME population (Arachie et al., 2023), found that awareness of generative AI and chatbot tools among surveyed SMEs was moderate, perceived usefulness for customer relationship management was consistently positive, but actual behavioural adoption remained low, a gap the authors describe as a disjuncture between cognitive alignment with AI's value and its translation into practice. A more recent contribution drawing on empirical data from 144 Nigerian SMEs similarly found that inadequate infrastructure, low digital literacy, skills shortages, and regulatory ambiguity were collectively preventing SMEs from moving beyond superficial engagement with AI, even as awareness continued to rise (TechBuild Africa, 2026). Several figures circulating in this literature, including double-digit efficiency gains attributed to individual firm case studies, are not drawn from representative samples, and this paper treats them as illustrative rather than generalisable.

What is largely absent from this literature, and what this paper attempts to address analytically rather than empirically resolve, is a sustained account of why the same barriers, infrastructure, skills, finance, keep recurring across studies conducted years apart and in different regions, without meaningful improvement. Most of the existing work treats these as a list of obstacles to be catalogued and then recommends, almost formulaically, "improved infrastructure" and "capacity building," without asking why previous rounds of similar recommendations have not shifted the underlying pattern. This paper takes that stasis itself as an object of analysis.

The awareness-integration gap and management support

A recurring theme across the reviewed studies is the moderating role of management support and, related to it, ownership structure. Nigerian SMEs are disproportionately owner-managed, and the decision to adopt any digital tool, AI-enabled or otherwise, tends to run through a single individual's risk tolerance and technical comfort rather than through a formal decision process. Akinruwa et al. (2025) find, using structural equation modelling on their Southwest Nigeria sample, that management support has a significant positive effect on SME performance and that employee capability itself contributes positively to management support, suggesting the two reinforce each other rather than operating as independent levers. This is broadly consistent with earlier findings from French manufacturing SMEs undergoing Industry 4.0 transformation, where managers were found to play a decisive role in whether such transformations succeeded or failed, and where a lack of managerial engagement, rather than the technology's cost or complexity alone, was identified as a central risk factor (Moeuf et al., 2020). The mechanism proposed is fairly intuitive: an owner-manager who understands, even partially, what an AI tool can and cannot do is more likely to allocate the often limited resources needed to integrate it properly, train staff to use it, and persist through the inevitable early friction of adoption, rather than abandoning the tool after a disappointing first attempt.

This matters for the argument developed later in this paper because it suggests that the performance effects of AI adoption are not primarily a function of the technology's inherent capability, which is broadly similar whether deployed in Lagos or Lisbon, but of organizational and managerial variables that vary considerably across Nigerian firms.

Infrastructural and institutional context

Nigeria's broadband penetration reached 43.71 percent by the end of 2023, according to the Nigerian Communications Commission's own year-end performance reporting (Nigerian Communications Commission, 2023), meaningful growth over the preceding decade but still short of the Commission's own 50 percent interim target for that year, and still leaving a substantial share of the population, and by extension a substantial share of SME customers and workers, outside reliable connectivity. Power supply remains, by most accounts, the single most cited operational constraint for Nigerian SMEs generally, predating and extending well beyond the AI adoption question, and it interacts with AI adoption directly: cloud-based tools require consistent connectivity, and firms with frequent outages either underuse what they have adopted or bear the added cost of backup power and data, eroding whatever efficiency gain the tool was meant to deliver.

The policy environment has moved, at least formally, to recognise digital transformation as a national priority. The National Digital Economy Policy and Strategy (2020–2030) frames digital adoption, including AI, as central to Nigeria's economic diversification strategy (Federal Ministry of Communications and Digital Economy, 2020). Whether this architecture has translated into SME-level support, financing instruments, training programmes, regulatory clarity around data use, is more contested, and several studies reviewed here note a persistent gap between stated policy ambition and implementation reality, a pattern familiar to anyone who has followed Nigerian digital policy over the past decade.

Theoretical Framework

This paper draws on two established frameworks, the Technology-Organization-Environment (TOE) framework and the Resource-Based View (RBV), used in combination rather than in isolation, on the grounds that neither is sufficient on its own to explain the Nigerian pattern.

Technology-Organization-Environment

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The TOE framework, originally developed by Tornatzky and Fleischer (1990), organises the determinants of technology adoption into three categories: technological factors (the perceived characteristics of the innovation itself, including relative advantage and complexity), organizational factors (firm size, managerial structure, slack resources, absorptive capacity), and environmental factors (competitive pressure, regulatory context, and the broader digital ecosystem within which the firm operates). The framework's durability across four decades of information systems research owes something to its flexibility; it does not specify in advance which factors will dominate in a given context, which makes it well suited to a setting like Nigeria where the relative weight of, say, environmental infrastructure versus organizational capacity is itself an empirical and contextual question rather than something the model presupposes.

Applied here, technological factors help explain why customer-facing AI tools, chatbots, automated social media scheduling, basic sentiment analysis, see faster and broader adoption than back-end applications such as predictive inventory systems or AI-assisted credit scoring: the former are lower in perceived complexity, cheaper to trial, and their relative advantage is more immediately visible to an owner-manager without technical training. Organizational factors, particularly the near-universal owner-management structure of Nigerian SMEs discussed above, help explain the persistence of the awareness-integration gap. Environmental factors, infrastructure quality, financing availability, regulatory ambiguity around data protection, help explain why adoption clusters geographically in ways that track broader patterns of urban digital infrastructure investment rather than tracking sectoral logic alone.

It is worth noting, however, a limitation in how TOE has typically been applied in the Nigerian SME literature reviewed above: most studies treat the three categories as additive and largely independent, running regressions or structural equation models that estimate separate coefficients for each. This misses what is arguably the more interesting dynamic, which is that the categories interact. Weak environmental infrastructure does not simply act as an independent brake on adoption; it actively degrades the technological factor of relative advantage, because a chatbot that is frequently offline due to connectivity failure delivers a much weaker value proposition than the same tool would in a stable-infrastructure environment, regardless of how the firm's management perceives it in the abstract. TOE-based Nigerian studies have generally not modelled this interaction explicitly, which this paper takes as an unresolved methodological gap rather than a settled matter.

Resource-Based View

The Resource-Based View, associated most closely with Barney (1991), argues that sustained competitive advantage derives from resources and capabilities that are valuable, rare, difficult to imitate, and non-substitutable. Applied to AI adoption, RBV shifts the analytical focus away from the technology itself, which is, after all, commercially available to any firm with an internet connection and modest capital, and toward the complementary organizational capabilities that determine whether a given firm can extract distinctive value from a widely accessible tool.

This matters considerably for the Nigerian case because it helps explain a pattern visible across several of the studies reviewed: firms that adopt broadly similar AI tools, often the same commercially available chatbot platforms or social media analytics dashboards, report divergent performance outcomes. If the technology were the primary source of advantage, this divergence would be harder to explain, since the tool itself is not differentiated across firms. RBV suggests instead that the differentiator lies in complementary capabilities, staff training, data literacy, the owner-manager's willingness to act on AI-generated insights rather than simply generating them, that are themselves unevenly distributed and, crucially, harder to build than the technology adoption decision itself. This reframes AI adoption not as the acquisition of a capability but as the acquisition of a tool that only becomes a capability once embedded in a set of organizational practices that many Nigerian SMEs, given resource constraints, have not yet developed.

A combined and cautious application

Neither framework, used alone, adequately captures the Nigerian pattern. TOE is strong on explaining variation in adoption but weaker on explaining variation in performance outcomes once adoption occurs, since it was developed primarily as an adoption model rather than a performance model. RBV is stronger on explaining why identical technologies produce divergent performance outcomes but says comparatively little about why adoption itself varies so much across the environmental conditions TOE foregrounds. Used together, with explicit awareness of their limitations rather than as an unquestioned analytical scaffold, they offer a more complete, if still partial, account: TOE explains who adopts and under what conditions, RBV explains why adoption translates into performance for some firms and not others. This paper does not claim to resolve the interaction problem identified above, but flags it as a direction future quantitative work in this specific context, ideally using structural equation modelling with explicit interaction terms, could usefully pursue.

Methodology

This paper adopts a qualitative research design based on thematic synthesis of published empirical and policy literature, rather than primary quantitative survey data. The reason is partly practical and partly principled. Practically, a further primary survey of Nigerian

SMEs on AI adoption would add another single-region, small-sample data point to a literature that already contains several such studies, Southwest Nigeria alone has been surveyed at least twice in the period under review, without necessarily resolving the interpretive questions this paper is concerned with. Principled reasons matter more: the central argument of this paper is not primarily about measuring the magnitude of AI's effect on performance, which existing survey-based studies have already attempted with reasonable rigour, but about interpreting why the pattern of effects looks the way it does across a body of existing evidence, and what that pattern implies theoretically and for policy. A synthesis approach is better suited to that interpretive task than a new primary survey would be.

Corpus and inclusion criteria

The corpus for this synthesis consists of peer-reviewed and credible grey-literature studies published between 2020 and 2026 addressing AI adoption, digital transformation, or SME performance with explicit reference to Nigeria or, for comparative purposes, other African or emerging-market contexts. Studies were included if they reported original empirical findings (survey data, case studies, or documented firm-level outcomes) or represented substantive policy documentation from recognised institutions, including SMEDAN, the National Bureau of Statistics, the Nigerian Communications Commission, and the Federal Ministry of Communications and Digital Economy. Studies confined to purely theoretical or promotional discussion of AI's potential, without empirical grounding, were used sparingly and only where they supplied useful conceptual framing rather than being treated as evidentiary sources in their own right.

This is a limitation the paper does not attempt to disguise. Several of the Nigeria-specific studies drawn upon here appear in journals with limited international indexing, and sample sizes across the regional studies range from under 150 to under 400 respondents, none of which supports claims of national representativeness. The synthesis approach adopted here treats convergence across independently conducted studies, rather than the statistical power of any single study, as the stronger basis for inference, on the reasoning that if the same barriers and the same awareness-integration gap recur across studies conducted in different regions, by different research teams, using different sampling frames, that convergence itself carries some evidentiary weight even where no individual study is methodologically strong.

Analytical approach

The paper uses thematic analysis in the tradition associated with Braun and Clarke (2006), applied to the corpus of secondary literature rather than to interview transcripts, a variant sometimes described as a thematic synthesis of secondary sources. Themes were developed inductively through repeated reading of the corpus, coded initially around descriptive categories, awareness levels, adoption rates, cited barriers, reported outcomes, sectoral concentration, and then refined into the analytical themes presented in section five through a process of constant comparison, checking emerging themes against the full corpus rather than settling on categories after an initial pass. Where quantitative figures are cited from the corpus, for instance adoption percentages or reported efficiency gains, they are reported as findings from the original studies rather than treated as this paper's own statistical evidence, and the paper is explicit throughout about the provenance and limitations of each figure.

Scope and limitations

The scope is limited in ways that should be stated plainly rather than buried. First, the corpus is geographically skewed toward Southern Nigeria, reflecting the existing literature's own skew, and this paper cannot correct for an absence of Northern Nigerian data that does not yet exist in adequate quantity. Second, the reliance on secondary synthesis means this paper cannot verify the methodological rigour of every underlying study beyond what is reported in the published work itself; where a study's sampling method or response rate raised concerns, this is noted in the text rather than silently incorporated. Third, the time horizon, 2020 to 2026, means the paper captures a period of rapid change in AI capability, particularly following the wider availability of generative AI tools from around 2022 onward, and adoption patterns documented in 2021 may not describe the same landscape as those documented in 2025; the paper attempts to date-stamp findings where this matters rather than treating the period as a single undifferentiated block.

Findings

Awareness has outpaced integration, consistently and by a wide margin

Across every regional study reviewed, self-reported awareness of AI tools among Nigerian SME operators sits considerably higher than measured or self-reported integration. The Southwest Nigeria study found 75 percent awareness against a considerably lower rate of demonstrated industry-specific understanding (Adegbuyi et al., 2024), and a comparable gap appears in the Southeast Nigeria data, where Arachie et al. (2025) found moderate awareness of generative AI and chatbot tools but low actual behavioural adoption despite a broadly positive perception of their usefulness, and in the more recent 144-firm study cited by TechBuild Africa (2026), which explicitly frames awareness as high and growing while adoption remains constrained by infrastructure, literacy, and skills gaps. This is not a Nigeria-specific anomaly; the German SME comparison found that only 5.8 percent of surveyed firms had actually applied AI despite considerably broader familiarity with the concept (Ulrich et al., 2021). What differs in the Nigerian case is less the existence of the gap than its persistence across multiple survey waves conducted years apart without apparent narrowing, which suggests the gap is not simply a lag effect that closes naturally with time, but reflects a more durable structural barrier.

Adoption is concentrated in low-complexity, customer-facing applications

Where Nigerian SMEs have moved beyond awareness into actual use, that use clusters heavily around a narrow set of applications: chatbots for customer service, automated or semi-automated social media marketing, and basic customer analytics. Deeper integrations, predictive inventory management, AI-assisted financial forecasting, automated supplier negotiation, appear in the literature almost exclusively as case-study examples from individual firms, often larger or better-capitalised than the median SME, rather than as a general pattern. This asymmetry is itself informative: it suggests that where AI delivers the clearest and most immediate gains for the typical Nigerian SME is precisely where the barrier to entry is lowest, in low-cost, low-complexity, customer-facing tools, rather than in the operationally deeper applications that would require greater capital, technical skill, and organizational restructuring to implement.

Infrastructure and finance function as binding constraints, not marginal frictions

The recurring citation of power supply unreliability, uneven broadband penetration (Nigerian Communications Commission, 2023), and constrained access to finance across nearly every study reviewed here suggests these are not marginal frictions that a sufficiently motivated firm can work around, but binding constraints that shape the ceiling of what AI adoption can achieve regardless of managerial enthusiasm. This matters analytically because much of the existing literature, and a good deal of the policy discourse around digital transformation in Nigeria, treats infrastructure and awareness as separate variables to be addressed through separate interventions. The findings synthesised here suggest they interact: an SME operator with high awareness and genuine enthusiasm for AI tools, operating in an area with unreliable connectivity, will show up in survey data as "aware but not adopting," which risks being read as a skills or attitude problem when it may in fact be substantially an infrastructure problem.

Management support and ownership structure moderate outcomes more than firm size alone

Several studies point to management support, and by extension the owner-manager's own digital comfort, as a stronger predictor of successful integration than firm size or sector. This is a modestly counterintuitive finding worth dwelling on: it implies that a smaller firm with a digitally literate, engaged owner-manager may extract more performance benefit from AI adoption than a somewhat larger firm with a more passive or technically disengaged management structure. The Southwest Nigeria evidence (Akinruwa et al., 2025) and the earlier French Industry 4.0 evidence (Moeuf et al., 2020) point in the same direction independently, which strengthens the case for treating management engagement, rather than firm size, as the more decisive variable, with real implications for how support programmes are targeted, discussed further in section six.

Regional and sectoral variation is substantial and under-theorised

The divergence between Southwest and Southeast Nigerian adoption patterns, and the sharper contrast with Ghana's more clearly documented marketing-focused AI adoption (Abrokwah-Larbi & Awuku-Larbi, 2024), indicates that "Nigerian SME" is too coarse a category for precise analysis. Sectoral variation compounds this: retail and consumer-facing service SMEs appear more likely to adopt customer-facing AI tools than manufacturing or agricultural SMEs, plausibly because the available low-cost tools are themselves designed primarily for customer interaction rather than production processes, a supply-side explanation that the demand-side framing common in adoption literature tends to underweight.

Analysis and Discussion

The findings assembled above resist a single tidy conclusion, and that resistance is itself analytically important. If AI adoption produced uniform performance gains across Nigerian SMEs, the policy prescription would be straightforward: subsidise adoption, remove friction, and gains would follow more or less automatically. What the evidence instead shows is a technology whose performance effects are almost entirely mediated by conditions that predate the technology itself and that AI adoption alone does nothing to resolve.

Consider the awareness-integration gap discussed in the findings section. The conventional policy response to such a gap is a training or capacity-building intervention, on the theory that operators who understand AI tools better will adopt them more readily. This is not wrong, but the evidence here suggests it addresses only part of the mechanism. An SME operator in a peri-urban area with unreliable power and patchy 4G coverage can be perfectly well informed about what a predictive inventory tool does and still find it operationally unusable, not because of a knowledge deficit but because the infrastructural substrate the tool requires is absent for a meaningful share of the working day. Training programmes that do not also address, or at minimum explicitly acknowledgs infrastructural ceiling risk raising awareness further without narrowing the adoption gap at all, which is precisely the pattern the literature has documented across multiple survey waves.

This connects to a broader critique that this paper wants to register against some of the more celebratory framing found in both consultancy reports and portions of the academic literature: the leapfrogging narrative, in its stronger form, implicitly assumes that digital technologies can substitute for physical infrastructure investment rather than depending on it. AI adoption research in Nigeria increasingly suggests the opposite, that AI's usefulness is downstream of, not a substitute for, reliable electricity and connectivity. This is not a novel observation in the broader digital transformation literature on sub-Saharan Africa; a scoping review of the region's SME digital transformation experience similarly found that infrastructural and institutional weaknesses, rather than firm-level attitudes toward technology, remain the dominant constraint on turning digital adoption into a genuine source of resilience (Achieng & Malatji, 2022). It deserves to be stated with more force in the specifically AI-focused literature, where the novelty and apparent sophistication of the technology sometimes seem to obscure how much its effectiveness still rests on unglamorous infrastructural foundations.

The RBV-informed finding on management support, carries an uncomfortable implication that the existing literature has not fully confronted. If a firm's capacity to extract value from AI adoption depends heavily on the owner-manager's own digital literacy and engagement, and if that literacy is unevenly distributed in ways correlated with education, urban location, and prior digital experience, then AI adoption support programmes that are technology-neutral in their targeting, offering the same training or subsidy to all applicant SMEs, will likely reproduce rather than narrow existing disparities. The firms best positioned to benefit from support are disproportionately those that would have adopted successfully with somewhat less support in the first place, while firms most in need of intervention, those with less digitally engaged ownership, are precisely the ones least likely to convert support into durable capability. This is a familiar problem in development economics more generally, sometimes discussed under the heading of the Matthew effect in innovation diffusion, but it has not been examined with much rigour in the Nigerian AI-adoption literature specifically, most of which treats management support as a variable to be measured rather than a distributional problem to be addressed.

There is also a methodological tension worth naming plainly rather than smoothing over. Isolated firm-level case studies reporting striking efficiency gains from AI adoption circulate widely in the secondary literature and in this paper's own sources, and their prominence risks creating an impression of typicality that the underlying evidence does not support. On the available evidence, these are examples of what is achievable under favourable conditions rather than descriptions of what is typically achieved, and the distinction matters for policy credibility. If policymakers or development partners set expectations around AI adoption's returns based on best-case examples rather than modal outcomes, the inevitable disappointment when broader adoption programmes fail to replicate those figures could undermine support for digital transformation initiatives that might otherwise be worth sustaining on more modest and more realistic terms.

None of this amounts to an argument against AI adoption in Nigerian SMEs, and it would be a mistake to read it that way. The customer-facing gains documented, improved responsiveness, more precisely targeted marketing, better customer data capture, are genuine and, in a market as competitively crowded as Nigerian urban retail and services, potentially significant even at a modest scale. The argument is narrower and, this paper would suggest, more useful than either wholesale endorsement or wholesale scepticism: AI adoption functions as a performance multiplier on existing organizational and infrastructural capacity, not as a substitute for it, and policy discourse that treats it as the latter is likely to be repeatedly disappointed by outcomes that in fact reflect entirely predictable constraints operating exactly as one would expect them to.

There is a further, more speculative point worth raising, even though the evidence base to test it rigorously does not yet exist. If AI tools increasingly mediate customer acquisition and retention, through algorithmically optimised marketing, automated customer service, and increasingly sophisticated recommendation systems embedded in the e-commerce platforms Nigerian SMEs sell through, then the competitive advantage such tools confer may accrue disproportionately to firms that adopted early and iteratively refined their use, generating a form of path dependency that later adopters cannot straightforwardly replicate simply by adopting the same tools. This would imply that the adoption timing gap documented throughout the literature is not merely a lag that will close as awareness spreads, but potentially a widening gap, in which early movers accumulate data, refine algorithms to their specific customer base, and build a form of tacit knowledge about tool use that is itself a resource meeting the RBV criteria of value and imperfect imitability. This is offered as a hypothesis rather than a finding, since none of the studies synthesised here tracked adoption timing longitudinally in a way that would allow it to be tested, but it strikes this paper as a more theoretically interesting question than most of the existing literature has posed, and one that future panel-data research on Nigerian SMEs could usefully investigate.

Conclusion

Artificial intelligence adoption among Nigerian SMEs sits at an uneasy midpoint between promise and constraint, and this paper has tried to take that unease seriously rather than resolve it into a cleaner story than the evidence supports. Awareness of AI tools is widespread and growing. Actual, deep integration remains the exception rather than the rule, concentrated in customer-facing applications where complexity is low and value is immediately visible, and largely absent from the back-end operational functions, inventory, credit assessment, production planning, where the largest efficiency gains might plausibly be found. The gap between these two facts is not primarily a knowledge problem, though knowledge gaps exist and matter; it is substantially an infrastructural and organizational problem that predates AI and that AI adoption alone cannot resolve.

The policy implication that follows is not a rejection of AI-focused digital transformation programming, but a call for more differentiated design. Programmes that bundle AI adoption support with realistic acknowledgment of infrastructural ceilings, rather than treating connectivity and power as background conditions to be assumed rather than addressed, are more likely to produce durable gains than awareness campaigns alone. Programmes that account explicitly for the uneven distribution of management digital literacy, rather than offering technology-neutral support that risks reinforcing existing capability gaps, are more likely to reach the firms that most need intervention rather than those that would have succeeded regardless.

This paper has been more cautious than celebratory, deliberately so, because the existing discourse around AI in African SMEs already tilts heavily toward celebration, often on the basis of global productivity figures describing a very different population of firms. That caution should not be mistaken for pessimism about the technology's eventual usefulness here. It reflects, instead, a judgment that the conditions under which AI adoption translates into genuine performance gains in Nigeria are still being built, unevenly and incompletely, and that research and policy attention would be better directed at those underlying conditions than at the adoption metric itself, which measures something shallower than the transformation it is often taken to represent.

Future research would benefit from longitudinal firm-level data that can track adoption timing and performance outcomes over multiple years rather than the cross-sectional snapshots that dominate the current literature, and from a more deliberate effort to include Northern Nigerian SMEs, whose near-total absence from the existing evidence base is itself a finding worth remarking on rather than an incidental gap.

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