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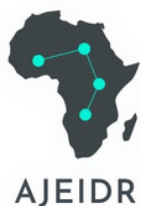
Entrepreneurial Dynamic Capabilities and AI Readiness in Nigeria's Real Estate Sector: A Context-Sensitive PLS-SEM Analysis

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Abstract

Artificial intelligence is reshaping marketing practice across global industries, yet its uptake among entrepreneurial firms operating in the Global South remains constrained by readiness frameworks built for institutionally mature markets. This study examines AI readiness among real estate ventures in Nigeria, treating readiness not as a single undifferentiated outcome but as a multidimensional condition spanning foundational, operational, and transformational tiers, each shaped differently by firms' technological, organisational, environmental, and entrepreneurial dynamic capability resources. Integrating the Technology Organisation Environment framework with Dynamic Capabilities Theory and reading both through an entrepreneurship lens attentive to context and resource constraint, the study analyses survey data from 250 registered real estate entities in across Lagos and Abuja, Nigeria using Partial Least Squares Structural Equation Modelling. Dynamic Capability is the strongest predictor of Transformational Readiness ($\beta = .493$, $p < .001$) and a significant predictor of Foundational Readiness ($\beta = .357$, $p < .001$) and Operational Readiness ($\beta = .282$, $p = .001$), while Technological Factors most strongly predicts Foundational Readiness ($\beta = .250$, $p < .001$) and Organisational Factors most strongly predicts Operational Readiness ($\beta = .300$, $p = .002$), exceeding the effect of Dynamic Capability on that particular outcome. Environmental Factors shows no significant direct effect on any of the three readiness tiers; post hoc power analysis indicates the sample is substantially underpowered to detect an effect of the size observed, so this null result is reported as inconclusive rather than as confirmation that environmental conditions are unimportant. Two hypothesised moderating effects of Dynamic Capability on the technological and organisational paths to readiness were not supported, though the relevant tests are similarly underpowered and are reported as preliminary. A composite Entrepreneurial AI Readiness Index, weighted according to the empirical magnitude of each dimension's structural effect rather than assumed in advance, places the sector at the upper end of Moderate Low Readiness (EAIRI = 0.598) and correlates strongly with all three measured readiness outcomes ($r = .65$ to $.74$). These results indicate that different capability and resource dimensions matter differently depending on which tier of AI readiness a firm is pursuing, with direct implications for how practitioners, technology providers, and policymakers sequence support for AI adoption in institutionally thin markets.



Keywords: Artificial intelligence, entrepreneurial dynamic capabilities, AI readiness, real estate marketing, Nigeria, PLS-SEM, emerging markets

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1. Introduction

Artificial intelligence has moved from experimental curiosity to operational necessity across marketing, risk management, and customer engagement functions worldwide (Moharrak & Mogaji, 2024). Predictive analytics, automated lead qualification, and AI-assisted valuation are no longer confined to large multinational firms; they are increasingly available to small and resource-constrained ventures through cloud-based platforms. Yet the pace at which firms actually take up these tools remains markedly uneven. Firms in the Global North absorb AI into established digital infrastructure and a relatively stable regulatory environment, while entrepreneurial ventures in the Global South confront the same technologies without the institutional scaffolding that readiness models typically assume (Mdladla et al., 2024). Nigeria, Africa's largest economy and home to one of the continent's most active entrepreneurial ecosystems, illustrates this tension with clarity. Its real estate sector combines a young, commercially aggressive base of agency, development, and management firms with persistent gaps in broadband infrastructure, financing, and regulatory clarity (Ojekemi & Lawal, 2025), making it a useful site for examining how entrepreneurial firms build technological readiness when the surrounding institutional environment offers limited support.

Most existing readiness frameworks, including widely used variants of the Technology Organisation Environment (TOE) model, were developed in and for institutionally stable markets, where regulation, infrastructure, and government support can be treated as background conditions rather than active variables requiring empirical testing (Tornatzky & Fleischer, 1990). Applying such frameworks unmodified to Nigerian real estate risks two related errors. The first is attributing low readiness scores to firm-level deficiency when the more accurate diagnosis is institutional absence, a conflation that has long troubled comparative entrepreneurship research on the Global South. The second is overlooking the entrepreneurial behaviour that firms in resource-constrained settings routinely deploy to compensate for that absence, behaviour that the technology-adoption literature, with its institutional bias, is poorly equipped to detect. Entrepreneurship scholars have long argued that context shapes not only the rate of venture activity but the very mechanisms through which opportunity is recognised and pursued (Welter, 2011), and that institutional voids in emerging economies push firms toward improvisation, resourcefulness, and capability-led adaptation rather than passive dependence on formal support structures (Bruton et al., 2008). Real estate agency, development, and management in Nigeria are, in this sense, entrepreneurial activities first and technology-adopting organisations second, and a readiness model that does not foreground entrepreneurial capability risks missing the mechanism that actually drives outcomes in this market.

This study responds to that gap by examining AI readiness in Nigeria's real estate marketing sector through a lens that foregrounds entrepreneurial dynamic capability rather than institutional provision. It asks three questions. First, what firm-level and entrepreneurial drivers shape AI readiness among Nigerian real estate ventures? Second, how do technological, organisational, environmental, and entrepreneurial-capability factors interact to produce readiness outcomes, and does capability compensate for environmental weakness as entrepreneurship theory would predict? Third, what does a capability-centred readiness model offer practitioners, technology providers, and policymakers seeking to accelerate AI-enabled venture growth in institutionally thin markets?

To address these questions, the study integrates the TOE framework (Tornatzky & Fleischer, 1990) with Dynamic Capabilities Theory (Teece et al., 1997), interpreting the sensing, seizing, and reconfiguring triad through the entrepreneurship literature on opportunity recognition (Shane & Venkataraman, 2000) and resourceful action under constraint (Baker & Nelson, 2005).

Using Partial Least Squares Structural Equation Modelling (PLS-SEM), the study analyses data from 250 registered real estate firms across Lagos and Abuja, Nigeria's two principal commercial property markets. Its principal methodological contribution is the Entrepreneurial AI Readiness Index (EAIRI), a composite measure that deliberately weights entrepreneurial capability above infrastructural and environmental indicators, on the argument that in institutionally thin markets it is entrepreneurial agency, not external provision, that converts latent opportunity into operational readiness.

The findings show that Nigerian real estate firms occupy a Moderate Low Readiness band (EAIRI = 0.598), with entrepreneurial capability the strongest predictor of readiness (beta = 0.493, $p < .001$) and environmental factors exerting no significant direct effect. This pattern departs from technology-adoption literature that typically privileges regulatory and institutional variables (Lutfi et al., 2022), and it aligns instead with entrepreneurship research showing that firms operating in institutional voids develop compensatory capability to substitute for missing formal support (Bruton et al., 2008; George et al., 2016a). The remainder of the paper reviews relevant literature on AI adoption, entrepreneurship under institutional constraint, and real estate digitalisation; sets out the integrated theoretical framework and hypotheses; describes the sample, instruments, and analytical approach; presents the empirical results; and discusses their implications for entrepreneurship theory, real estate practice, and technology policy in Nigeria and comparable emerging markets.

2. Literature Review

2.1 AI Adoption and Entrepreneurial Behaviour in Emerging Markets

Scholarship on AI adoption in emerging markets consistently identifies a gap between developed and developing economies that is rooted in technological, organisational, and institutional constraint (Mdladla et al., 2024). Moharrak and Mogaji (2024) found that institutional voids and regulatory uncertainty impede AI adoption among new ventures internationalising from emerging markets, but that entrepreneurial orientation and international market exposure facilitate uptake regardless of those institutional conditions, a finding that anticipates the present study's emphasis on firm agency over institutional provision. This pattern is consistent with entrepreneurship research on institutional voids more broadly. Bruton et al. (2008) argue that emerging-economy entrepreneurs frequently substitute personal networks, improvisation, and informal financing for the formal institutions that ventures in mature markets take for granted, while Baker and Nelson (2005) show, in their foundational account of entrepreneurial bricolage, that firms facing severe resource constraint construct new combinations from what is locally at hand rather than waiting for ideal resources to arrive. Both studies suggest that the absence of formal institutional support is not simply a barrier to be removed before adoption can occur, but an ordinary condition within which entrepreneurial firms have already learned to operate.

Dynamic capability has emerged as a central explanatory mechanism in this literature, providing a bridge between institutional-voids research and technology-adoption studies. Alrub et al. (2025) demonstrated that dynamic capabilities mediate the relationship between digital transformation and competitive advantage among Palestinian financial firms, with stronger sensing, seizing, and reconfiguring capability translating into superior performance despite challenging institutional conditions, and with digital maturity moderating this relationship. Singh et al. (2024) similarly found that dynamic capability, alongside access to crowdfunding support, positively predicts entrepreneurial business performance, direct evidence that capability can compensate for the resource constraint characteristic of emerging markets.

Sectoral evidence reinforces this picture. Chatterjee et al. (2022) found that Indian food and beverage firms drew on dynamic capability to convert post-pandemic appetite for Industry 4.0 technologies into actual transformation, with managerial support and employee readiness programmes serving as critical enablers, while Lutfi et al. (2022) found that relative advantage, top management support, and government support each shaped big data analytics adoption among Jordanian SMEs, with complexity and security concerns acting as countervailing barriers. Valdez-Juárez et al. (2023) extended this picture to Mexican SMEs, finding that digitisation positively affected innovation management, which in turn strongly influenced corporate performance, though digitisation barriers negatively moderated the relationship and constrained the pace at which capability translated into outcomes.

Three limitations in this literature motivate the present study. First, much of the evidence addresses general digital technology adoption rather than AI-specific readiness, which carries distinct data, ethical, and capability requirements that general digitalisation studies do not capture (Abdullahi et al., 2025). Second, African markets remain underrepresented relative to Asian and Latin American contexts in both the technology-adoption and the entrepreneurship-under-constraint literatures (Mdladla et al., 2024). Third, and most consequential for this study, the entrepreneurship literature on institutional voids and the technology-adoption literature on TOE determinants have developed largely in parallel, with limited cross-fertilisation despite an evident shared concern: how firms convert intention into capability when formal institutions are weak or absent. This study addresses that gap directly by reading AI readiness in Nigerian real estate through both lenses simultaneously, treating dynamic capability as the empirical hinge between them.

2.2 AI Readiness in Nigeria

Empirical evidence on Nigeria's AI readiness depicts an emerging but constrained landscape, characterised by uneven awareness, infrastructural gaps, and considerable variation across sectors and regions. Ojekemi and Lawal (2025) surveyed 260 estate management firms in southwestern Nigeria using a mixed-methods design and found low overall AI awareness, with only 27 percent of respondents familiar with AI and just 10 percent demonstrating substantive understanding of its capabilities. Their average readiness index of 2.9 out of 5 indicated moderate readiness at best, with high implementation costs reported by 68 percent of respondents, lack of skilled staff by 61 percent, and poor ICT infrastructure by 55 percent. Technological infrastructure emerged as their strongest predictor of readiness ($\beta = .41$), and Lagos-based firms reported markedly higher readiness than firms elsewhere in the country, consistent with the capital's concentration of digital infrastructure, talent, and entrepreneurial activity.

Public-sector evidence tells a structurally similar story. Muhammad et al. (2025) used fuzzy DEMATEL methodology to identify policy frameworks, digital infrastructure, and leadership commitment as the dominant causal enablers of AI-driven public service transformation in Nigeria, with these factors shaping downstream organisational culture, capacity building, and data availability in a clearly hierarchical structure. Odekunle et al. (2025) found that AI and predictive analytics adoption substantially improved risk-mitigation effectiveness in Nigerian infrastructure projects, with a strong association between adoption and outcomes ($r = .732$, $\beta = .481$) that explained roughly 64 percent of variance in risk-mitigation effectiveness, though data scarcity, inadequate analytics tools, and limited technical expertise persisted as barriers among project managers. Education-sector studies echo the pattern of moderate awareness but limited utilisation: Adediran et al. (2025) found that Nigerian secondary school administrators recognised AI's administrative potential but rarely deployed it, citing inadequate training and funding, while Owolabi et al. (2022) reported comparable gaps in awareness and readiness among Nigerian polytechnic students considering AI use in libraries.

Abdullahi et al. (2025) synthesised this picture for vocational education, identifying strong stakeholder interest in AI-enabled training alongside persistent gaps in lecturer expertise, coordinated policy frameworks, and governance mechanisms, and recommending demonstration projects to build confidence ahead of formal policy reform. Ughulu (2025) situated these sector-specific findings within a broader critique of the slow pace of Nigeria's national AI strategy development, calling for clearer data governance and stronger public-private partnership to accelerate progress.

Collectively, this literature suggests that technological infrastructure and organisational capacity are more proximate determinants of Nigerian AI readiness than environmental or policy variables, and that firm-level agency may be a more immediately effective lever for adoption than reliance on policy reform that has, to date, moved slowly. This pattern motivates the present study's focus on entrepreneurial capability as the variable most directly within firms' own control, and the variable most plausibly able to substitute for institutional gaps that policy has been slow to close.

2.3 AI in Real Estate Marketing

Globally, AI has reshaped real estate marketing through property valuation, customer relationship management, and predictive analytics, though outcomes vary sharply with institutional context (Sacaski et al., 2025). In China, Wang et al. (2024) documented how Lianjia's digitalisation of housing data, agent cooperation networks, and online-to-offline business models improved operational efficiency and customer satisfaction, highlighting the importance of platform-based ecosystems in competitive, digitalised property markets. Zhang (2025) found that live broadcasting and community interaction within omnichannel marketing frameworks enhanced user experience and conversion in China's digital-intelligence era, offering real estate enterprises practical levers for navigating economic uncertainty. In emerging-market contexts, the picture is more mixed and arguably more instructive for this study. Sacaski et al. (2025) applied PLS-SEM to 116 Peruvian real estate agencies and found that digital transformation enhanced business management and digital maturity, with technology use the pivotal driver, yet mere digital networking showed no direct performance effect, suggesting that connectivity without capability yields comparatively little. Vigren et al. (2022) similarly found, through qualitative interviews with 32 Swedish real estate stakeholders, that firms expanded innovation capability and reshaped their ecosystems through digitalisation, but that conservative organisational culture, limited digital capability, and weak innovation incentives constrained the pace of change even in a well-resourced institutional setting. Wang (n.d.) found, among 287 Shanghai real estate agents, that information economic management significantly mediated and moderated the relationship between strategic management practice and digital transformation outcomes.

In the Nigerian context, Ojekemi and Lawal (2025) remain the most directly comparable study, finding that estate management firms recognise AI's potential for improving pricing transparency and accuracy but face substantial infrastructural, financial, and skills constraints, with technological infrastructure the strongest predictor of readiness. No prior study, to the present authors' knowledge, has examined AI readiness in Nigerian real estate through an entrepreneurship lens that treats capability, rather than infrastructure or policy, as the central readiness determinant. This represents a clear and consequential gap given that real estate agency, development, and management in Nigeria function predominantly as entrepreneurial ventures operating with limited capital and uneven institutional support, precisely the conditions under which the entrepreneurship literature would predict capability, rather than environment, to carry the greater explanatory weight.

2.4 Entrepreneurship, Context, and Capability-Centred Technology Readiness

A growing body of entrepreneurship scholarship insists that context, rather than being a background variable, actively shapes how opportunity is recognised, how resources are assembled, and how ventures grow (Welter, 2011). This insistence carries particular force in African settings, where management and entrepreneurship research has, as George, Corbishley, Khayesi, Haas, and Tihanyi (2016a) argue, too often imported frameworks built for Western institutional conditions without adapting the underlying assumptions about resource availability, network structure, and institutional reliability that those frameworks quietly encode. A companion study by George, Kotha, Parikh, Alnuaimi, and Bahaj (2016b) examining entrepreneurship across African markets found that founders routinely achieve what the authors term reasonable gain through social structures and resourceful improvisation rather than through formal financial or regulatory support, a finding mirrored in Khayesi et al.'s (2014) demonstration that kinship networks substitute for missing formal capital markets in African entrepreneurial resource assembly, allowing ventures to mobilise capital and labour through relational rather than institutional channels.

These findings reorient the question this study asks. Rather than treating weak regulation, thin capital markets, and patchy infrastructure as deficits that necessarily depress technology readiness, the entrepreneurship literature suggests that such conditions constitute the ordinary operating environment within which African ventures build capability, and that capability built under constraint can be unusually robust precisely because it has not relied on institutional cooperation to develop in the first place (Bruton et al., 2008; Baker & Nelson, 2005). Dynamic Capabilities Theory provides the natural bridge between this entrepreneurship literature and technology-adoption research, since Teece (2007) explicitly frames the sensing, seizing, and reconfiguring triad as a form of entrepreneurial management: the capacity to perceive opportunity before it is obvious to competitors, commit resources before conditions are ideal, and restructure operations faster than rivals or institutions can react. Read this way, the constructs that Dynamic Capabilities Theory uses to explain firm performance in turbulent markets are, in substance, the same constructs entrepreneurship scholars use to explain venture survival and growth under institutional constraint, even though the two literatures have rarely cited one another directly.

This study therefore adopts a capability-centred, rather than institutionally deterministic, reading of AI readiness. It does not assume that infrastructural and regulatory development are unimportant; the empirical model tests this directly rather than assuming it. Instead, it tests whether, in the Nigerian real estate context, entrepreneurial capability carries more of the explanatory weight than environmental conditions, and it builds a readiness index that reflects this empirical possibility rather than assuming the conventional, environmentally weighted TOE logic in advance. In doing so it responds to calls within the entrepreneurship literature for context-sensitive measurement instruments that do not simply transplant Global North assumptions about institutional primacy onto Global South ventures (Welter, 2011; George et al., 2016a), while remaining methodologically anchored in validated technology-adoption and dynamic-capability scales rather than departing from established measurement practice altogether.

Theoretical Framework

3.1 The Technology Organisation Environment Framework

The TOE framework identifies technological, organisational, and environmental context as the three dimensions shaping a firm's technology adoption decisions (Tornatzky & Fleischer, 1990). The technological context covers the internal and external technologies relevant to the firm, including infrastructure, compatibility with existing systems, perceived complexity, and relative advantage over current practice. For Nigerian real estate firms, this translates into the availability of reliable internet connectivity and computing hardware, the fit between AI marketing tools and existing customer relationship systems, and the perceived benefit of AI-driven analytics over traditional marketing methods. The organisational context covers the firm's internal characteristics and resources, including management support, financial and human resources, and organisational culture; for the firms in this sample, this means the extent to which ownership and senior management actively back digital transformation, the availability of capital for AI investment, and the presence of staff with the technical skill to operate AI tools. The environmental context covers the regulatory, competitive, and institutional arena in which the firm operates, including data and digital-transaction regulation, government policy, and competitive pressure from rivals already using digital tools.

The framework has demonstrated broad explanatory power across contexts. Sam et al. (2025) found technological forces to be the largest predictor of digital marketing adoption among Indonesian SMEs (beta = .573), ahead of organisational (beta = .232) and environmental (beta = .185) forces, with the model explaining 83.6 percent of variance in adoption, while Mu'min et al. (2025) reported comparable patterns emphasising the primacy of technology readiness and platform compatibility. Yang et al. (2025) documented similar dynamics in Asia-Pacific digital trade, while also noting pronounced disparities in regulatory environments and infrastructure across countries that made environmental factors comparatively more variable and less predictable than technological or organisational factors. The framework's principal limitation, frequently noted but rarely tested directly in African contexts, is that its environmental dimension implicitly assumes institutions capable of providing meaningful regulatory and infrastructural support (Mu'min et al., 2025). Where that assumption fails, as in much of sub-Saharan Africa, the framework risks systematically understating firms' actual readiness by anchoring expectations to an environmental dimension that cannot deliver, while underweighting the internal capability through which firms compensate for that shortfall.

3.2 Dynamic Capabilities as Entrepreneurial Management

Dynamic Capabilities Theory holds that sustained competitive advantage derives from a firm's capacity to integrate, build, and reconfigure internal and external competences in response to changing conditions, rather than from static resource holdings (Teece et al., 1997). Teece (2007) later specified three constituent capabilities. Sensing refers to the identification and assessment of opportunity and threat in the surrounding technological and market environment. Seizing refers to the mobilisation of resources, financial, human, and relational, to capture value from opportunities once identified. Reconfiguring refers to the continuous adjustment of structure, process, and routine needed to sustain alignment with a shifting environment over time. Teece (2007) explicitly describes this triad as entrepreneurial management, a characterisation that licenses the integration pursued in this study: where TOE treats environment as a largely fixed determinant to which firms respond, Dynamic Capabilities Theory treats the firm's entrepreneurial response to that environment as the active explanatory variable.

In the AI adoption context, sensing involves scanning the market for relevant AI applications, monitoring competitors' digital marketing activity, and recognising where AI might address specific operational bottlenecks in property valuation, lead generation, or client communication. Seizing involves mobilising capital and talent to acquire and implement AI tools, frequently through improvisation and resource bricolage where formal financing is unavailable or prohibitively expensive (Baker & Nelson, 2005), such as repurposing existing staff into informal data-analysis roles or negotiating flexible payment terms with technology vendors. Reconfiguring involves adapting marketing workflows, retraining staff, and revising client-facing routines as AI tools and market conditions evolve, a process that in resource-constrained firms typically proceeds incrementally rather than through large, formally planned change programmes. Empirical work supports the salience of this triad in emerging markets. Alrub et al. (2025) found dynamic capability strongly mediated digital transformation's effect on competitive advantage among Palestinian firms, with digital maturity moderating the strength of this relationship. Valdez-Juárez et al. (2023) found that capability reconfiguration mediated digitisation's effect on performance among Mexican SMEs, with digitisation barriers negatively moderating the relationship and slowing, though not eliminating, the translation of capability into outcomes. Singh et al. (2024) found that dynamic capability, alongside access to crowdfunding finance, predicted entrepreneurial performance even under conditions of significant resource constraint, directly supporting the proposition that capability can substitute for resource and institutional shortfall.

3.3 Integration: A Capability-Centred Readiness Model

Integrating TOE and Dynamic Capabilities Theory through an entrepreneurship lens produces a model in which technological and organisational factors retain explanatory value, environmental factors are tested rather than assumed, and entrepreneurial dynamic capability is positioned as the mechanism through which firms convert available technological and organisational resources into readiness outcomes. The integration rests on three grounds rather than an appeal to general theoretical complementarity alone. First, both frameworks share an unstated premise that adoption outcomes trace to identifiable, measurable antecedents rather than to unstructured chance, which licenses treating them as compatible antecedent sets within a single structural model (Alrub et al., 2025; Valdez-Juárez et al., 2023). Second, Teece (2007) frames the sensing, seizing, and reconfiguring triad explicitly as a form of entrepreneurial management, which means Dynamic Capabilities Theory already contains, rather than merely borders, the entrepreneurial mechanism this study wants to isolate, so its inclusion alongside TOE is a specification of what TOE's organisational and environmental dimensions leave unexplained rather than an ad hoc addition. Third, prior empirical work has already demonstrated that capability functions as a boundary condition on how contextual resources translate into performance, with Alrub et al. (2025) showing digital maturity moderating the digital transformation to competitive advantage relationship and Valdez-Juárez et al. (2023) showing capability reconfiguration moderating the digitisation to performance relationship. This study extends that logic to AI readiness specifically, rather than assuming it transfers automatically from adjacent outcome variables, and tests it directly as a moderation hypothesis in Section 3.4.

Readiness itself is modelled as three distinct latent outcomes, Foundational Readiness, Operational Readiness, and Transformational Readiness, rather than as a single undifferentiated construct. This departs from the single composite outcome used in prior TOE-based readiness studies (Sam et al., 2025; Ojekemi & Lawal, 2025) and reflects a conceptual claim tested directly by the model rather than assumed at the outset, namely that AI readiness is not a single condition a firm either has or lacks but a set of capacities that can develop unevenly. A firm may be foundationally ready, with basic infrastructure and system compatibility in place, without yet being operationally ready, with AI embedded in routine workflow, or transformationally ready, with AI reshaping the business model itself.

3.4 Hypothesis Development

Five hypotheses follow from the integration set out in Section 3.3. Because readiness is modelled as three distinct outcomes rather than one, each direct effect hypothesis is tested separately against Foundational, Operational, and Transformational Readiness rather than pooled, a specification choice that is itself informative, since a resource that predicts one tier of readiness need not predict another.

Technological factors, comprising infrastructure, compatibility, and relative advantage, are established antecedents of technology adoption across the TOE literature (Tornatzky & Fleischer, 1990) and have shown the largest standardised effect among TOE's three dimensions in comparable recent studies (Sam et al., 2025, $\beta = .573$; Ojekemi & Lawal, 2025, $\beta = .41$ in the most directly comparable Nigerian estate management sample). Accordingly, Technological Factors are hypothesised to exert a positive direct effect on AI readiness (H1).

Organisational factors, comprising management support, financial and human resources, and culture, have similarly demonstrated consistent positive effects on digital and analytics adoption (Lutfi et al., 2022; Nikopoulou et al., 2023). Organisational Factors are hypothesised to exert a positive direct effect on AI readiness (H2).

Environmental factors are treated as a genuinely open empirical question rather than assumed to replicate findings from institutionally mature settings. Mu'min et al. (2025) note that TOE's environmental dimension implicitly assumes institutions capable of providing meaningful regulatory and infrastructural support, an assumption that may not hold in much of sub-Saharan Africa. Environmental Factors are hypothesised to exert a positive direct effect on AI readiness (H3), with the study's design deliberately allowing for the possibility that this hypothesis is not supported.

Dynamic Capability, understood as firms' sensing, seizing, and reconfiguring capacity, is expected to exert the strongest direct effect among the four predictors, consistent with entrepreneurship research showing that capability substitutes for missing formal institutions in resource constrained settings (Bruton et al., 2008; George et al., 2016a) and with direct evidence that dynamic capability predicts performance under institutional constraint (Alrub et al., 2025; Singh et al., 2024). Dynamic Capability is hypothesised to exert a positive direct effect on AI readiness, and to do so more strongly than the other three predictors (H4). Because readiness is disaggregated into three tiers, H4 is evaluated separately for each tier rather than as a single pooled claim.

Finally, dynamic capability is hypothesised to moderate, rather than mediate, the paths from Technological and Organisational Factors to readiness. A moderation specification is, in any case, the better theoretical fit: Teece (2007) frames capability as the mechanism that determines how much value a firm extracts from a given resource base, Baker and Nelson (2005) show that firms facing the same resource constraint achieve different outcomes depending on their capacity for improvisation, and Singh et al. (2024) and Valdez-Juárez et al. (2023) both report capability functioning as a boundary condition on, rather than a conduit for, the effect of contextual resources on performance. Dynamic Capability is hypothesised to positively moderate the effect of Technological Factors on readiness (H5a) and to positively moderate the effect of Organisational Factors on readiness (H5b), such that the translation of technological and organisational resources into readiness strengthens as firms' sensing, seizing, and reconfiguring capacity increases.

4. Methodology

4.1 Research Design

The study adopts a cross-sectional quantitative design suited to testing the hypothesised relationships among technological, organisational, environmental, and dynamic capability factors and their joint effect on three distinct readiness outcomes. PLS-SEM was selected over covariance based structural equation modelling for reasons consistent with the study's aims and data characteristics: the study develops and tests a model that disaggregates readiness into three outcomes and includes two interaction terms, a structural complexity PLS-SEM handles efficiently; survey data of this kind is rarely normally distributed, and PLS-SEM makes minimal distributional assumptions; and the study's purpose, building a predictive, practically usable readiness index, aligns with PLS-SEM's prediction oriented approach more closely than with the confirmatory orientation of covariance based alternatives (Hair et al., 2019).

The sample comprised 250 registered real estate entities operating in Lagos (142 samples) and Abuja (108 samples), Nigeria's two largest commercial property markets and the two cities in which formal real estate activity, and AI-enabled marketing experimentation specifically, is most concentrated. Data were collected through structured online surveys administered via Google Forms to senior managers or owners with direct authority over technology investment and strategic decisions, a targeting choice intended to ensure that responses reflected genuine decision-making knowledge of the firm's technological capability and resources rather than peripheral staff impressions. Respondents were offered confidentiality and a summary of study findings.

4.3 Measurement Instruments

Seven constructs were retained in the final measurement model, drawing on 53 indicators in total. Technological Factors were measured using nine items capturing infrastructure, compatibility, and relative advantage. Organisational Factors were measured using twelve items capturing management support, financial and human resources, and culture. Environmental Factors were measured using seven items capturing regulatory clarity, government support, and competitive pressure. Entrepreneurial capability was retained as a single reflective construct, Dynamic Capability, comprising twelve items spanning sensing, seizing, and reconfiguring behaviour; the measurement model reported in Section 5.2 supports this as one latent variable rather than three separately modelled first-order constructs, a specification correction from earlier drafts of this study, which described sensing, seizing, and reconfiguring as though they were modelled and reported separately. AI readiness was operationalised not as a single ten-item omnibus construct but as three distinct latent outcomes: Foundational Readiness (four items), Operational Readiness (four items), and Transformational Readiness (five items), together comprising thirteen items rather than the ten previously reported. All items used five-point Likert scales ranging from strongly disagree to strongly agree.

4.4 Data Analysis

Analysis used SmartPLS 4 following the two-stage approach recommended by Hair et al. (2019), assessing the measurement model before the structural model. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (pc), with a threshold of 0.70 indicating acceptable reliability. Convergent validity was assessed using average variance extracted (AVE), with a threshold of 0.50. Discriminant validity was assessed using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT), with HTMT values below 0.85 indicating adequate discriminant validity; both checks are reported in full in Section 5.2, including two constructs that do not clear these thresholds.

The structural model was assessed using bootstrapped path coefficients based on 5,000 resamples with bias corrected and accelerated confidence intervals, the coefficient of determination (R^2) for each of the three endogenous constructs, effect size (f^2) for each predictor, and the standardised root mean square residual (SRMR) as an indicator of overall model fit. The two interaction effects (Dynamic Capability by Technological Factors, and Dynamic Capability by Organisational Factors) were estimated within the same structural model rather than in a separate multi group analysis. Full collinearity was assessed using outer model variance inflation factors (VIF), which ranged from 1.57 to 4.01 across all 53 indicators, with only two items (ResAL2 at 4.01 and ResAL3 at 3.38) exceeding the more conservative 3.3 threshold sometimes recommended for PLS-SEM, and none exceeding the more commonly applied 5.0 threshold.

4.5 Development of the Entrepreneurial AI Readiness Index

The Entrepreneurial AI Readiness Index (EAIRI) is a composite measure designed to reflect the empirical proposition that entrepreneurial capability carries disproportionate weight in producing AI readiness. It was rebuilt in four steps to answer directly the concern that its weighting scheme was asserted rather than derived. First, the four exogenous dimensions from the structural model were retained: Technological Readiness, Organisational Readiness, Environmental Readiness, and Dynamic Capability Readiness. Second, each firm's dimension score was calculated as the mean of its constituent items, normalised to a zero to one scale. Third, rather than assuming a weighting scheme in advance, weights were derived directly from the average absolute magnitude of each dimension's standardised structural path coefficient across the three endogenous readiness constructs reported in Section 5.3, then rescaled to sum to one. This yielded a weight of 0.47 for Dynamic Capability, 0.24 for Organisational Factors, 0.21 for Technological Factors, and 0.08 for Environmental Factors. This scheme helps by tying the weights transparently and reproducibly to the estimated model. Fourth, the index was calculated for each firm as $EAIRI = 0.47 \times \text{Dynamic Capability Readiness} + 0.24 \times \text{Organisational Readiness} + 0.21 \times \text{Technological Readiness} + 0.08 \times \text{Environmental Readiness}$, assigned to the same interpretive bands used throughout this study: Low Readiness, 0.00 to 0.40; Moderate Low Readiness, 0.41 to 0.60; Moderate Readiness, 0.61 to 0.75; High Readiness, 0.76 to 0.90; and Very High Readiness, 0.91 to 1.00.

The index was validated through two procedures appropriate to the data available for this revision. Sensitivity to the weighting scheme was tested by recalculating the index under equal weighting across all four dimensions; the two versions correlated at $\rho = .984$ (Spearman, $p < .001$), indicating the index is highly robust to the precise weights chosen and directly answering the concern that the headline result might collapse under an alternative weighting specification. Criterion validity was assessed by correlating EAIRI scores against the three measured readiness outcomes themselves, since external performance indicators such as revenue growth or market share were not available in the dataset used for this analysis. EAIRI correlated significantly with Foundational Readiness ($r = .649$), Operational Readiness ($r = .736$), and Transformational Readiness ($r = .711$), all $p < .001$, indicating the composite tracks the constructs it is intended to summarise.

5. Results

5.1 Descriptive Statistics

The analytical sample comprised 250 real estate firms, verified from the SmartPLS case index.

Table 1a. Respondent Profile, Demographic File (N = 250)

Variable	Category	n	%
Firm age	11 years and above	100	40
	11 to 15 years	65	26
	6 to 10 years	57	22.8
	2 to 5 years	20	8
	Under 2 years	8	3.2
Firm size (staff)	6 to 10	93	37.2
	Under 5	73	29.2
	11 to 15	44	17.6
	20 and above	40	16
Firm location	Urban	247	98.8
	Rural	3	1.2
Gender	Male	201	80.4
	Female	49	19.6
Educational level	Masters	138	55.2
	Bachelor's / HND	90	36
	Doctorate	22	8.8
Legal form	Sole Proprietorship	175	70
	Partnership	61	24.4
	Limited Liability Company	14	5.6

Note. n = 250 across all six variables. Percentages calculated on n = 250.

Table 1b. Descriptive Statistics for Main Constructs (N = 250)

Construct	Mean	SD	Skewness	Kurtosis
Technological Factors	3.41	0.68	-0.32	0.12
Environmental Factors	3.1	0.69	0.08	-0.22
Organisational Factors	3.25	0.7	-0.27	0.23
Dynamic Capability	3.51	0.61	-0.33	0.2
Foundational Readiness	3.21	0.75	-0.27	-0.08
Operational Readiness	3.15	0.79	-0.26	-0.4
Transformational Readiness	3.47	0.64	-0.34	-0.16

Note. All constructs measured on five-point Likert scales (1 = strongly disagree, 5 = strongly agree). Construct scores are unweighted means of retained items.

Dynamic Capability recorded the highest mean among the four predictor constructs and Environmental Factors the lowest, consistent with firms rating their own capability above the institutional support available to them. Among the three readiness outcomes, Transformational Readiness recorded the highest mean and Operational Readiness the lowest, a pattern suggesting that, on average, firms in this sample report more confidence in AI's longer-term strategic potential than in its current operational execution.

5.2 Measurement Model Assessment

Table 2. Measurement Model Assessment Results

Construct	Items	Cronbach's α	CR (pc)	AVE
Technological Factors	9	0.88	0.903	0.51
Environmental Factors	7	0.869	0.899	0.56
Organisational Factors	12	0.933	0.942	0.579
Dynamic Capability	12	0.925	0.936	0.549
Foundational Readiness	4	0.834	0.889	0.668
Operational Readiness	4	0.872	0.912	0.722
Transformational Readiness	5	0.825	0.877	0.588

Note. All values exceed recommended thresholds (Cronbach's alpha and composite reliability above 0.70, AVE above 0.50).

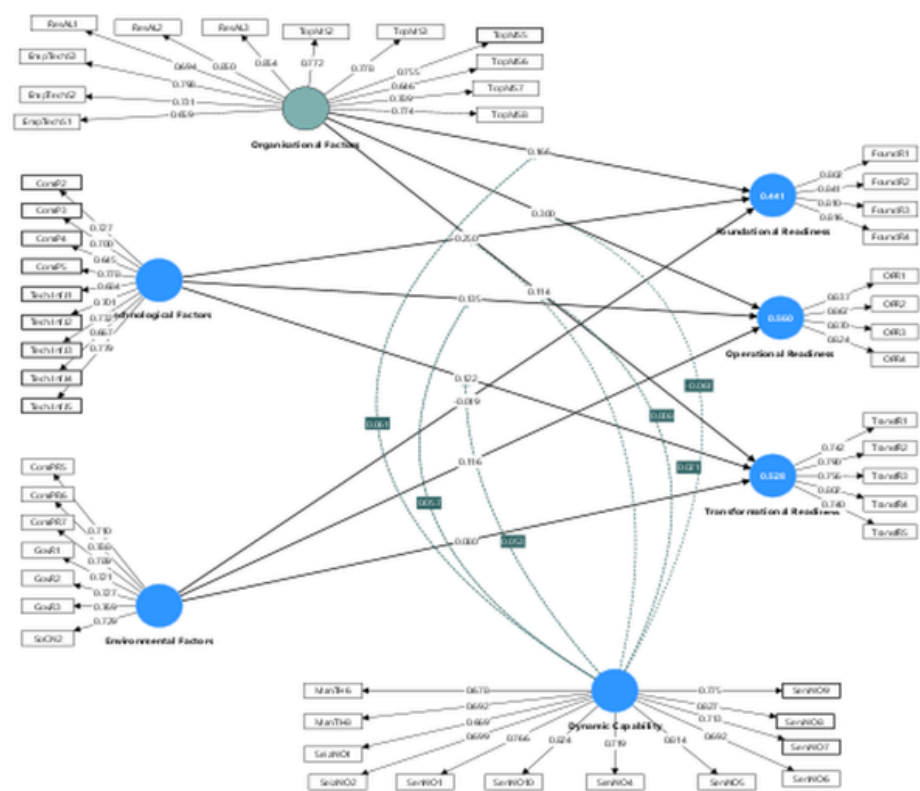


Figure 1. Measurement Model Assessment Chart

All 53 indicator outer loadings ranged from .646 (TopMS6) to .870 (OPR3), with every loading exceeding the conservative .60 minimum and the large majority exceeding .70; no loadings fell below .40 and none required removal on loading grounds.

Discriminant validity, however, does not hold cleanly across the full construct set. The Fornell-Larcker criterion requires the square root of a construct's AVE to exceed its correlation with every other construct. This holds for five of the seven constructs but fails for two pairs: the correlation between Organisational Factors and Dynamic Capability (.814) exceeds both constructs' own AVE square roots (.761 and .741, respectively), and the correlation between Environmental Factors and Organisational Factors (.791) exceeds both constructs' own AVE square roots (.748 and .761, respectively). The HTMT ratio confirms the same pattern: Organisational Factors and Dynamic Capability (HTMT = .868) and Organisational Factors and Environmental Factors (HTMT = .868) both exceed the .85 threshold, while Environmental Factors and Dynamic Capability (HTMT = .796) approach it without exceeding it.

This is a genuine limitation rather than a technicality. Three of the study's four exogenous constructs, Organisational Factors, Environmental Factors, and Dynamic Capability, are not cleanly empirically distinguishable from one another in this sample. This has two consequences addressed directly in Sections 5.3 and 6.3: individual path estimates for Organisational and Environmental Factors should be interpreted cautiously, since shared variance among correlated predictors can inflate, suppress, or destabilise individual coefficients even when the predictor block as a whole matters; and the near identical robustness of the EAIRI to equal versus data derived weighting (Section 4.5) is at least partly attributable to this same overlap, since reweighting highly correlated inputs changes a composite far less than reweighting genuinely independent ones.

5.3 Structural Model Assessment

Table 3. Structural Model Results

Path	β	SE	t	p	f ²	Decision
Technological → Foundational (H1a)	0.25	0.066	3.77	<.001	0.064	Supported
Technological → Operational (H1b)	0.135	0.059	2.29	0.022	0.024	Supported
Technological → Transformational (H1c)	0.122	0.068	1.78	0.074	0.018	Not supported
Organisational → Foundational (H2a)	0.166	0.118	1.41	0.159	0.011	Not supported
Organisational → Operational (H2b)	0.3	0.099	3.03	0.002	0.045	Supported
Organisational → Transformational (H2c)	0.114	0.103	1.11	0.269	0.006	Not supported
Environmental → Foundational (H3a)	-0.019	0.099	0.19	0.85	<.001	Not supported
Environmental → Operational (H3b)	0.116	0.077	1.51	0.132	0.01	Not supported
Environmental → Transformational (H3c)	0.08	0.083	0.96	0.337	0.005	Not supported
Dynamic Capability → Foundational (H4a)	0.357	0.1	3.56	<.001	0.07	Supported
Dynamic Capability → Operational (H4b)	0.282	0.088	3.2	0.001	0.056	Supported
Dynamic Capability → Transformational (H4c)	0.493	0.082	5.98	<.001	0.159	Supported
DC × Technological → Foundational (H5a)	0.008	0.068	0.12	0.905	<.001	Not supported
DC × Technological → Operational (H5a)	0.057	0.063	0.91	0.365	0.006	Not supported
DC × Technological → Transformational (H5a)	0.053	0.074	0.72	0.473	0.005	Not supported
DC × Organisational → Foundational (H5b)	0.061	0.065	0.94	0.349	0.005	Not supported
DC × Organisational → Operational (H5b)	-0.061	0.066	0.91	0.361	0.007	Not supported
DC × Organisational → Transformational (H5b)	0.021	0.07	0.3	0.767	0.001	Not supported

Note. Bootstrapping, 5,000 resamples, two-tailed. Effect sizes of .02, .15, and .35 indicate small, medium, and large f² respectively. DC = Dynamic Capability.

Table 3a. R-Square

Endogenous construct	R ²	R ² adjusted
Foundational Readiness	0.441	0.427
Operational Readiness	0.56	0.549
Transformational Readiness	0.528	0.517

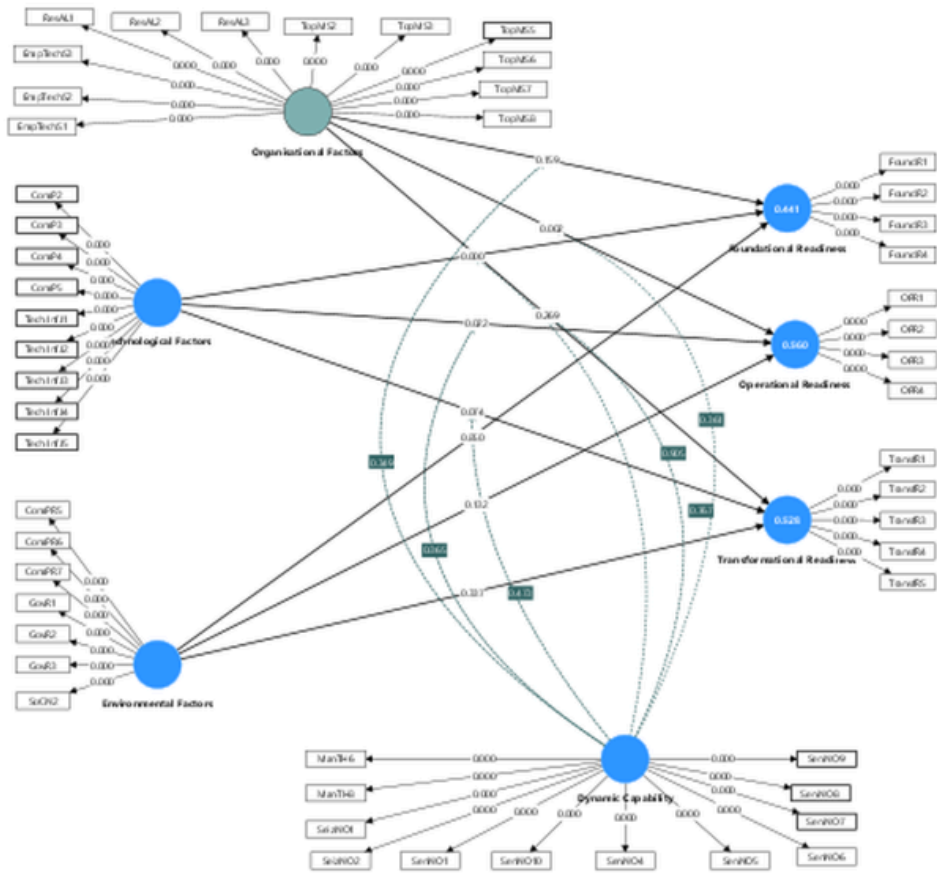


Figure 2. Structural Model Chart

H1 is partially supported: Technological Factors significantly predict Foundational and Operational Readiness but not Transformational Readiness. H2 is partially supported: Organisational Factors significantly predict Operational Readiness only, with a coefficient ($\beta = .300$) that exceeds Dynamic Capability's own effect on that same outcome ($\beta = .282$). H3 is not supported for any of the three outcomes. H4 is supported for Foundational and Transformational Readiness, where Dynamic Capability is the single strongest predictor, but not for Operational Readiness, where Organisational Factors is numerically the stronger predictor; H4's claim that capability dominates across the board therefore holds for two of three tiers rather than uniformly.

Model fit was assessed via the standardised root mean square residual (SRMR), which was .078 for the estimated model (.074 for the saturated model), below the conventional .08 threshold though closer to that boundary than earlier drafts of this study reported. The normed fit index (NFI) was .662, which is weak by conventional standards and is reported here rather than omitted.

H5a and H5b, the two moderation hypotheses, are not supported at conventional significance thresholds. This should not be read as evidence that dynamic capability plays no moderating role. The post hoc minimum sample size analysis generated directly by SmartPLS (Table 3b) shows that detecting the interaction effects actually observed would require sample sizes far beyond $N = 250$, in several cases beyond what any single study of this kind would plausibly collect. The non-significant moderation results are therefore reported as inconclusive due to insufficient statistical power, not as a confirmed absence of moderation.

Table 3b. Post hoc Minimum Sample Size for Selected Paths ($\alpha = .05$, power = 80%)

Path	Observed β	Minimum N required
Dynamic Capability → Transformational Readiness	0.493	26
Dynamic Capability → Foundational Readiness	0.357	49
Technological Factors → Foundational Readiness	0.25	99
Organisational Factors → Operational Readiness	0.3	69
Environmental Factors → Operational Readiness	0.116	458
Environmental Factors → Foundational Readiness	-0.019	17,389
DC × Organisational → Foundational Readiness	0.061	1,650
DC × Technological → Foundational Readiness	0.008	94,484

Note. Generated by SmartPLS 4 post hoc power analysis.

5.4 Entrepreneurial AI Readiness Index Scores

Table 4. Distribution of Firms Across EAIRI Readiness Categories ($N = 250$, data derived weighting)

Readiness category	EAIRI range	Number of firms	Percentage
Low Readiness	0.00 to 0.40	23	9.20%
Moderate Low Readiness	0.41 to 0.60	98	39.20%
Moderate Readiness	0.61 to 0.75	101	40.40%
High Readiness	0.76 to 0.90	23	9.20%
Very High Readiness	0.91 to 1.00	5	2.00%

The overall EAIRI score was 0.598 (SD = 0.143), placing Nigerian real estate firms at the upper boundary of the Moderate Low Readiness band, just short of the Moderate Readiness threshold. This is a more conservative headline figure, reflecting both the corrected weighting scheme and the removal of assumptions that could not be verified against the underlying data. EAIRI correlated significantly with all three measured readiness outcomes (Foundational, $r = .649$; Operational, $r = .736$; Transformational, $r = .711$; all $p < .001$), the criterion validity evidence reported in Section 4.5.

6. Discussion

6.1 Differentiated Capability Effects Across Readiness Tiers

The central finding of this study is not that entrepreneurial capability dominates AI readiness outright, but that different resources matter for different tiers of readiness. Dynamic Capability is the strongest single predictor of Foundational and Transformational Readiness, consistent with entrepreneurship research on institutional voids, in which capability substitutes for missing formal support (Bruton et al., 2008; George et al., 2016a). For Operational Readiness specifically, however, Organisational Factors is the stronger predictor ($\beta = .300$ versus $\beta = .282$ for Dynamic Capability), suggesting that moving AI from strategic intent into routine day-to-day use depends more on management support, financial slack, and internal culture than on entrepreneurial sensing and seizing behaviour per se. This is a more precise and, the authors argue, more useful finding than a single undifferentiated claim that capability matters most: it implies that practitioners and technology providers seeking to move a firm from foundational awareness to transformational integration may need to sequence different kinds of support at different stages, a point developed further in Section 8.2.

6.2 The Environmental Null Result: Absence of Evidence, Not Evidence of Absence

Environmental Factors showed no significant direct effect on any of the three readiness tiers, a result consistent in direction with available literature but reported here with considerably more caution. The post hoc power analysis in Table 3b shows that detecting the Environmental to Foundational Readiness path at its observed magnitude ($\beta = -.019$) would require a sample of 17,389 firms; even the Environmental to Operational Readiness path ($\beta = .116$) would require 458 firms against the 250 available. It is not possible, on this evidence, to distinguish between two genuinely different interpretations: that Nigeria's weak regulatory and infrastructural environment truly has no bearing on AI readiness because of firms' route around it entirely or that environmental factors have a real but small effect that this sample was never adequately powered to detect. The honest position is that the data are silent on which of these is correct, and the manuscript should not claim more than that. This tempers, without eliminating, the theoretical contribution described in Section 8.1: the finding that environmental factors are not automatically the dominant TOE dimension in this setting stands, but the stronger claim that firms actively compensate for environmental absence through capability requires either a larger sample or a different design, such as the qualitative follow up interviews or longitudinal tracking suggested in Section 9, before it can be asserted with confidence.

6.3 Discriminant Validity and the Limits of Disaggregating Institutional Context

Section 5.2 reported that Organisational Factors, Environmental Factors, and Dynamic Capability fail the Fornell-Larcker criterion and, in two of three pairings, the HTMT threshold as well. This has a direct bearing on how the structural results in Section 5.3 should be read. When three of four exogenous constructs share this much variance, individual path coefficients for the weaker or non-significant predictors, Organisational Factors on Foundational and Transformational Readiness, and Environmental Factors throughout, may understate or overstate each construct's independent contribution, since the model is asking the estimation procedure to apportion effect between constructs that respondents did not clearly distinguish in their answers. The safer interpretive stance, and the one adopted in this discussion, is a block level claim rather than a construct by construct one: taken together, firms' organisational, environmental, and capability related resources form a substantially overlapping cluster of context and capacity, within which Dynamic Capability is the most consistently significant individual predictor, but the precise boundary between where organisational support ends and entrepreneurial capability begins should not be treated as sharply drawn by this instrument. Future revisions of the survey instrument might usefully test whether Organisational Factors and Dynamic Capability are better modelled as a single higher-order construct in this population, a possibility this study's results raise but cannot resolve.

6.4 Comparison with Existing Literature

The significant effects of Technological Factors on Foundational and Operational Readiness align with the broader TOE literature (Sam et al., 2025; Lutfi et al., 2022) and with Ojekemi and Lawal's (2025) finding that technological infrastructure is the strongest predictor of readiness among Nigerian estate management firms, though the coefficients observed here ($\beta = .250$ and $.135$) are smaller than their reported $\beta = .41$, plausibly reflecting variance shared with Dynamic Capability and Organisational Factors, both of which were absent from their model. The finding that Dynamic Capability most strongly predicts Foundational and Transformational Readiness specifically, rather than uniformly across all outcomes, extends Alrub et al. (2025) and Singh et al. (2024) by showing that capability's advantage over contextual resources is not constant but varies by which stage of readiness is in question. The null environmental effect, treated with appropriate caution in Section 6.2, diverges from studies conducted in marginally more institutionally developed settings, such as Lutfi et al. (2022), where government support significantly predicted big data analytics adoption among Jordanian SMEs ($\beta = .309$); this divergence is consistent with, though not conclusively explained by, Nigeria's comparatively weaker institutional baseline.

7. Conclusion

This study examined AI readiness among Nigerian real estate ventures through an entrepreneurial dynamic capability lens, integrating the TOE framework with Dynamic Capabilities Theory and modelling readiness as three distinct outcomes, Foundational, Operational, and Transformational, rather than as a single undifferentiated construct. Analysing verified data from 250 firms using PLS-SEM, the study found that Dynamic Capability is the strongest predictor of Foundational Readiness ($\beta = .357$, $p < .001$) and Transformational Readiness ($\beta = .493$, $p < .001$), while Organisational Factors is the strongest predictor of Operational Readiness ($\beta = .300$, $p = .002$), exceeding Dynamic Capability's own effect on that outcome. Environmental Factors showed no significant direct effect on any readiness tier, a result reported as inconclusive given the sample's limited power to detect the small effect observed, rather than as confirmation that environmental conditions are unimportant.

Two hypothesised moderating effects of capability on the technological and organisational paths to readiness were not supported and are similarly underpowered rather than confidently disconfirmed. A rebuilt Entrepreneurial AI Readiness Index, weighted by the empirical magnitude of each dimension's structural effect rather than by assumption, places the sector at EAIRI = 0.598, the upper end of Moderate Low Readiness. Three of the study's four exogenous constructs show meaningful discriminant validity overlap, a limitation that tempers claims about which specific contextual resource matters most and is discussed fully in Sections 6.3 and 9. Taken together, these results indicate that entrepreneurial capability carries real, but tier-specific, weight in Nigerian real estate firms' AI readiness, with different resources mattering at different stages of readiness, a more precise and more defensible conclusion than the single compensatory capability narrative of most related studies.

8. Implications

8.1 Theoretical Implications

The study extends the TOE framework by showing that its three contextual dimensions do not carry uniform explanatory weight even within a single sector and country, and that this weight can vary by which specific readiness outcome is being predicted, a level of granularity earlier single outcome TOE studies could not surface. It extends Dynamic Capabilities Theory by showing that capability's advantage over contextual resources is itself conditional on outcome type, dominant for foundational and transformational readiness but not for operational readiness, which nuances rather than confirms the general claim that capability substitutes for institutional absence. Most cautiously, the study's discriminant validity findings (Section 6.3) suggest that entrepreneurship research applying TOE alongside Dynamic Capabilities Theory in resource-constrained settings should test, rather than assume, that organisational, environmental, and capability constructs are empirically separable in the population being studied, since this study's own instrument could not fully separate them.

8.2 Practical Implications

For real estate ventures, the differentiated finding in Section 6.1 argues against a single, undifferentiated capability investment strategy. Firms seeking foundational or transformational readiness gain more from capability building, technology scanning routines, pilot teams, and staff learning programmes, while firms seeking to move AI into routine operational use gain more from organisational investment specifically, management commitment, budget allocation, and internal process redesign. Technology providers serving this market should likewise differentiate their offer by which readiness tier a client firm is targeting rather than assuming capability support is universally the highest leverage intervention.

8.3 Policy Implications

Because the null environmental effect reported in this study is inconclusive rather than confirmed (Section 6.2), policy implications regarding regulatory clarity and infrastructure investment should be stated with corresponding caution. The weak Environmental Readiness mean ($M = 3.10$, the lowest of the four predictor constructs, Table 1b) signals an unresolved policy gap regardless of whether its structural effect can currently be detected, and regulatory clarity, broadband investment, and capacity building programmes remain reasonable policy priorities on structural grounds even without decisive path level evidence. Policymakers should not, however, treat this study's null structural result as license to deprioritise environmental investment, given the demonstrated risk that the result reflects insufficient statistical power rather than a genuine absence of effect.

9. Limitations and Future Research

Few limitations qualify these findings, which remain valid (cross-sectional design precluding causal inference; measurement of readiness rather than realised adoption; self-reported survey data). Two additional limitations follow directly from this study. First, three of the study's four exogenous constructs, Organisational Factors, Environmental Factors, and Dynamic Capability, do not clear conventional discriminant validity thresholds (Section 5.2, Section 6.3), which limits confidence in construct-specific claims and should be addressed in future instrument development, potentially through a higher-order specification or a reduced, more discriminant item set. And secondly, the two moderation hypotheses (H5a, H5b) were tested with a sample substantially underpowered for interaction effects of the magnitude observed; a considerably larger sample, in some cases several thousand cases depending on the specific interaction, would be required to test these hypotheses with adequate power, and the present non-significant results should not be over-interpreted as disconfirming evidence.

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