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DIGITAL ENTREPRENEURIAL INTELLIGENCE IN EMERGING ECONOMIES: AN MIS CONCEPTUAL FRAMEWORK FOR DIGITAL VALUE CREATION IN NIGERIA

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ABSTRACT: Despite accelerating investments in enterprise digital transformation, empirical evidence regarding the link between digital technology adoption and sustainable competitive advantage remains fragmented and inconclusive. Management Information Systems (MIS) scholarship has traditionally prioritised the acquisition of technological assets and the development of data infrastructure, leaving a critical theoretical gap in understanding the internal mechanisms by which firms systematically convert digital information abundance into strategic entrepreneurial action. This gap is particularly noticeable in emerging economies like Nigeria, where rapid, platform-driven digitalisation coexists with systemic institutional uncertainty, infrastructural constraints, and acute resource instability. To address these theoretical and contextual limitations, this paper develops Digital Entrepreneurial Intelligence (DEI) as a novel, higher-order organisational dynamic capability. We create a thorough, multifaceted conceptual framework by combining viewpoints from Dynamic Capabilities Theory, Organisational Information Processing Theory (OIPT), the Knowledge-Based View (KBV), Absorptive Capacity Theory, and Entrepreneurial Cognition. Environmental Scanning Intelligence, Digital Analytics Intelligence (DAI), Opportunity Recognition Intelligence, Innovation Evaluation Intelligence, and Adaptive Intelligence are the five distinct dimensions that make up DEI. The study develops a theoretically based model that illustrates how management skills and digital information resources drive the growth of DEI, which in turn improves firm-level innovation capability and long-term organisational competitiveness. We conclude by delivering a rigorous future empirical validation roadmap, which includes exact statistical power analysis calculation for structural equation modelling and comprehensive psychometric scale development phases.

Keywords: Digital Entrepreneurial Intelligence, Management Information Systems, Dynamic Capabilities, Digital Entrepreneurship, Emerging Economies, Nigeria

INTRODUCTION

The contemporary global economy is increasingly defined by rapid digitalisation, hyper-connectivity, and an unprecedented proliferation of data resources. Across modern organisational landscapes, enterprises have access to enormous streams of real-time information generated by digital platforms, business systems, social media channels, Internet of Things (IoT) architectures, and advanced data analytics tools (Laudon & Laudon, 2022). Tracking how the adoption of these digital technologies improves internal operational efficiencies, streamlines supply chain networks, and reduces structural transaction costs has historically received significant scholarly attention within the Management Information Systems (MIS) discipline (Vial, 2019). However, a closer examination of the broader empirical literature reveals a frustrating paradox: the clear link between the use of digital technology and sustainable long-term performance benefits remains conflicting, fragmented, and inconclusive (Bharadwaj et al., 2013; Warner & Wäger, 2019).

This persistent discrepancy draws attention to a crucial organisational issue. While digital technologies have successfully democratised access to large networks of information, many organisations lack the internal competencies needed to translate this information abundance into distinct entrepreneurial achievements (Nambisan, 2017). Instead, organisations often succumb to extreme information overload, decision-makers' cognitive exhaustion, and strategic paralysis. The issue is now the inability to identify which data signals are important, what those signals suggest about the market's future, and how to allocate resources to capture the associated value, rather than a lack of data access.

This operational bottleneck is dramatically magnified within the setting of emerging economies, most notably in Nigeria. Due to the rapid expansion of fintech platforms, mobile commerce apps, digital entrepreneurial endeavours, and technology-mediated ecosystems, Nigeria has become a major centre of digital expansion throughout Sub-Saharan Africa over the last ten years (Adeosun & Shittu, 2022; World Bank Group, 2019). Yet, these digitally active Nigerian businesses must constantly carry out their plans while negotiating severe institutional gaps, unstable macroeconomic swings, uneven regulatory frameworks, and persistent physical infrastructure deficiencies, like unstable power supplies and disjointed broadband networks (Afolayan & Olanrewaju, 2021).

In such extremely volatile and resource-constrained environments, standard digital technology adoption or access to raw data streams no longer serves as a source of competitive advantage. This is due to the fact that fundamental digital tools and software solutions spread quickly across markets; they are heavily commercialised and are easily replicated by competitors. Consequently, an enterprise's true competitive differentiator does not reside in the technological assets it owns but in its internal organisational capability to cut through digital noise, isolate weak market signals, interpret ambiguous ecological shifts, and transform raw data pipelines into valid, actionable entrepreneurial choices (Teece, 2007; Warner & Wäger, 2019).

Although foundational frameworks in management and MIS literature, like Organisational Information Processing Theory (Galbraith, 1974), Absorptive Capacity Theory (Cohen & Levinthal, 1990; Zahra & George, 2002), and Dynamic Capabilities Theory (which includes sensing, seizing, and transforming routines; Teece, 2007), provide structural lenses for understanding organisational adaptation, they are still too abstract and compartmental. They describe what an organisation needs to accomplish in order to stay flexible, but they do not offer a comprehensive explanation of the micro-foundations that allow organisations to methodically transform digital data into entrepreneurial results while carrying out their regular business operations.

To bridge this theoretical gap, this paper introduces the construct of Digital Entrepreneurial Intelligence (DEI). Digital Entrepreneurial Intelligence (DEI) is an overarching, sophisticated organisational capability that empowers firms to leverage digital data streams for competitive advantage. It operates by systematically gathering, processing, and synthesising diverse information assets, thereby enabling organisations to proactively identify emerging market opportunities, critically assess the viability of technological innovations, and dynamically reconfigure their strategic architecture to align with volatile digital environments (Galbraith, 1974; Teece, 2007). This study is carefully structured as a conceptual and theory-building work rather than as a preliminary or partial empirical report based on future data collection. By describing the informational micro-foundations of sensing and seizing capacities, it directly contributes to ongoing scholarly discussions in Management Information Systems (MIS) and digital entrepreneurship. It offers a rigorous theoretical framework that clarifies how digital information abundance is converted into organisational innovation and long-term competitiveness in evolving market settings.

THEORETICAL BACKGROUND AND LITERATURE SYNTHESIS

To construct a rigorous and coherent foundation for Digital Entrepreneurial Intelligence, the discussion must move beyond a sequential listing of historical frameworks and instead develop an integrated theoretical synthesis. This section therefore examines five influential theoretical traditions that are central to MIS, strategy, organisational learning, and digital entrepreneurship: Dynamic Capabilities Theory, Organisational Information Processing Theory, the Knowledge-Based View, Absorptive Capacity Theory, and the Entrepreneurial Cognition perspective. Each framework contributes an important but partial explanation of how firms adapt, process information, generate knowledge, learn from external environments, and recognise entrepreneurial opportunities. However, when considered separately, these perspectives do not fully explain how digitally active firms, particularly in emerging economies, convert large volumes of fragmented digital information into innovation choices and sustained competitiveness. By critically reviewing their contributions and limitations, this section demonstrates why DEI is needed as an integrated, higher-order construct that links digital information processing with entrepreneurial interpretation, strategic evaluation, and adaptive organisational action.

Dynamic Capabilities Theory

Originally conceptualised to explain how firms sustain competitive advantage in high-velocity environments, Dynamic Capabilities Theory emphasises an organisation’s capacity to purposefully adapt, reconfigure, gain, and release its asset base to match changing market environments (Teece, 2007). The framework categorises these activities into three core clusters of routines: sensing market shifts, seizing identified opportunities, and transforming (or reconfiguring) organisational structures (Teece, 2007; Teece et al., 2016).

While this theory has become a dominant lens within contemporary digital transformation research, it faces significant criticism for its high level of abstraction and tautological tendencies (Wilden et al., 2016). Scholars often note that dynamic capabilities are frequently defined by their outcomes, meaning a firm is assumed to possess dynamic capabilities simply because it survived a market disruption. The framework outlines what a firm must do to remain flexible, but it offers limited insight into the exact informational mechanisms or cognitive processes required to perform sensing and seizing inside a data-saturated digital ecosystem.

Furthermore, traditional dynamic capabilities literature was developed before the widespread adoption of modern big data analytics, automated platform algorithms, and decentralised digital networks. In a digitalised economy, sensing cannot rely solely on the informal intuition of a few executive leaders; it must be built into repeatable, data-driven organisational systems (Yoo et al., 2010). DEI directly addresses this limitation by detailing the precise information-processing micro foundations that enable sensing and seizing routines in modern digital environments.

Organisational Information Processing Theory (OIPT)

Organisational Information Processing Theory treats an enterprise as an open system that must continuously process information to manage environmental uncertainty and complete tasks (Galbraith, 1974). The core tenet of OIPT is that organisational performance optimises when a firm's internal information-processing capabilities perfectly match the information-processing demands imposed by its external environment (Galbraith, 1974). Environmental uncertainty is defined as the difference between the amount of information already possessed by the firm and the amount of information required to execute a strategic task.

In the modern digital landscape, the introduction of advanced data channels dramatically increases information-processing demands. While technology adoption expands data pipelines, it simultaneously increases environmental complexity by inundating managers with unverified, unstructured data signals. OIPT provides a critical lens for this study: it demonstrates that technology adoption alone does not resolve uncertainty. If a firm expands its data inflows without upgrading its internal cognitive processing capabilities, it experiences information overload, which degrades strategic performance.

DEI serves as the missing organisational capability within OIPT. It provides the structured cognitive routines required to filter, synthesise, and interpret these intensified information flows, ensuring that expanded data pipelines actually reduce strategic uncertainty rather than increasing operational confusion.

The Knowledge-Based View (KBV) of the Firm

The Knowledge-Based View (KBV) extends the resource-based view by positing that knowledge is the primary, strategically significant resource capable of generating a sustainable competitive edge (Grant, 1996). Because knowledge is inherently complex, socially embedded, and difficult for rivals to imitate, its effective exploitation enables a firm to outperform its competitors (Grant, 1996). KBV distinguishes between explicit knowledge (data that can be easily codified and shared) and tacit knowledge (experiential, deeply contextual insights that are difficult to articulate).

In digitalised business environments, the challenge lies in converting explicit digital data points into tacit strategic knowledge. Raw metrics on a dashboard are merely explicit inputs. Strategic advantage occurs only when an organisation applies contextual interpretation to those metrics, transforming them into shared organisational knowledge regarding customer pain points or market trends (Wade & Hulland, 2004). DEI operationalises the core tenets of KBV by serving as the organisational engine that continuously processes raw, explicit digital information inputs and converts them into deeply contextualised, tacit strategic knowledge that can guide entrepreneurial action.

Absorptive Capacity Theory

Closely aligned with the Knowledge-Based View, Absorptive Capacity Theory explains a firm's ability to recognise the value of new, external information, assimilate it, transform it, and apply it to commercial ends (Cohen & Levinthal, 1990; Zahra & George, 2002). This capability is traditionally conceptualised as a four-stage process: acquisition, assimilation, transformation, and exploitation (Zahra & George, 2002).

While absorptive capacity provides an excellent framework for analysing general organisational learning and research and development (R&D) cycles, it has notable limitations when applied to fast-moving digital platform ecosystems. Traditional absorptive capacity research focuses primarily on how firms internalise formalised, structured scientific knowledge or technological innovations from external partners. It does not explicitly account for how firms handle unverified, fragmented, and fast-moving behavioural signals generated on digital platforms.

Furthermore, absorptive capacity models often assume a linear progression of learning that lacks an explicit focus on *entrepreneurial discovery*. In highly volatile digital spaces, a firm cannot wait for full, linear knowledge assimilation; it must possess an aggressive capability to recognise and validate fleeting commercial opportunities mid-stream. DEI extends absorptive capacity theory by reorienting these learning routines specifically toward rapid entrepreneurial discovery, selection, and strategic agility.

The Entrepreneurial Cognition Perspective

Historically, entrepreneurship literature treats opportunity recognition as an individual-level phenomenon that depends heavily on the founder's personal background, unique intuition, alertness, or cognitive biases. While this perspective provides useful insights for small start-ups, it is inadequate for understanding digital entrepreneurship within established organisations or scaling enterprises (Nambisan, 2017).

In data-intensive markets, opportunity identification shifts from an individualistic, subjective trait to an organisational-level capability (Yoo et al., 2010). Insights are no longer found solely through personal intuition; they are systematically uncovered through the alignment of data integration pipelines, analytics dashboards, automated feedback loops, and regular, cross-functional managerial interpretation routines.

DEI operationalises this shift, moving entrepreneurial cognition away from a chaotic personal characteristic and embedding it into repeatable, institutionalised organisational practices. By synthesising these five theoretical perspectives, we show that DEI sits at a vital intersection: it uses OIPT to manage data inflows; Absorptive Capacity and KBV to transform those inflows into knowledge; and Dynamic Capabilities and Entrepreneurial Cognition to execute that knowledge as strategic market actions.

CONCEPTUAL DEVELOPMENT OF DIGITAL ENTREPRENEURIAL INTELLIGENCE

To establish a rigorous conceptual framework, we must clearly define Digital Entrepreneurial Intelligence and demonstrate its distinct discriminant validity. Without a precise analytical differentiation, any new construct risks appearing redundant against well-established concepts in the literature. This is especially important in MIS and digital entrepreneurship research, where related terms such as analytics capability, competitive intelligence, knowledge management, absorptive capacity, and dynamic capabilities are often used interchangeably despite reflecting different organisational routines. DEI must therefore be positioned not as another label for digital technology use, but as a higher-order intelligence capability that explains how firms interpret digital signals, evaluate opportunity relevance, and translate information into entrepreneurial action. Clarifying these boundaries strengthens the theoretical legitimacy of the construct and ensures that subsequent hypotheses are anchored in a conceptually distinct mechanism. Accordingly, this section first differentiates DEI from adjacent constructs before specifying its internal dimensions and operational logic.

Construct Differentiation and Boundaries

A major concern in MIS and management research is ensuring that DEI does not merely rename existing constructs. Its boundary is clearest when separated from Data Analytics Capability: Data Analytics Capability refers to the technical and structural IT infrastructure that enables data capture, storage, processing, and modelling, including the software, hardware, databases, algorithms, and code that make analytics possible. By contrast, Digital Analytics Intelligence (DAI) is not the infrastructure itself; it is the cognitive and organisational human routine through which managers cross-reference analytical outputs, compare multiple data sources, interpret patterns, and convert them into strategic entrepreneurial decisions. Table 1 therefore carries the detailed comparison, while this section foregrounds the core distinction between technical analytics infrastructure and intelligence-based strategic interpretation.

Table 1 provides an analytical map detailing the boundaries and distinctiveness of DEI against these adjacent constructs.

Table 1: Conceptual Boundaries and Distinctiveness of DEI

Construct	Primary Conceptual Focus	Core Strategic Question	Primary Theoretical Limitation
Dynamic Capabilities (Teece, 2007)	High-level asset reconfiguration and structural adaptation routines.	How do we adapt our organisational assets to survive market shifts?	Remains highly abstract; lacks specific micro-foundations regarding digital information interpretation.
Absorptive Capacity (Zahra & George, 2002)	Systematic external knowledge acquisition, assimilation, and internalisation.	How do we learn from external sources and internalise that knowledge?	Focused primarily on linear R&D learning cycles; lacks explicit focus on rapid entrepreneurial opportunity discovery.

Data Analytics Capability (Mikalef et al., 2020)	Technical and structural IT infrastructure: analytics software, hardware, databases, algorithms, code, data engineering, statistical modelling, and processing architecture.	What patterns, trends, or predictions can our technical analytics infrastructure generate from data sets?	Technology-centric; provides the analytical infrastructure but not the human, cognitive, and organisational routines needed for strategic entrepreneurial decision-making.
Competitive Intelligence (Hughes, 2020)	Tracking, monitoring, and countering the tactical behaviours of market rivals.	What are our direct competitors doing, and how do we respond?	Primarily reactive and defensive; limited focus on cross-industry business model innovation.
Knowledge Management (Alavi & Leidner, 2001)	Systematically archiving, retrieving, and distributing internal knowledge.	How do we capture and share our existing organisational knowledge?	Internally and historically oriented; lacks the high-velocity agility required for disruptive platforms.
Digital Entrepreneurial Intelligence (DEI) (Proposed Construct)	Cognitive and organisational routines for cross-referencing multi-channel digital information, interpreting analytical outputs, and selecting strategic entrepreneurial actions.	How do we interpret, cross-reference, and act on digital information to make valid innovation choices?	Addresses these gaps by integrating information-processing routines with strategic entrepreneurial execution.

Delineating the Five Dimensions of DEI

We conceptualise Digital Entrepreneurial Intelligence as a higher-order, multi-dimensional organisational capability composed of five distinct, yet interrelated dimensions. Each dimension represents a specific organisational routine that handles a particular phase of the digital information conversion process.

Environmental Scanning Intelligence

Environmental Scanning Intelligence refers to an organisation's capability to continuously monitor, track, and filter complex technological, competitive, market, and regulatory disruptions across diverse digital ecosystems (Laudon & Laudon, 2022). In a highly volatile digital market like Nigeria, changes occur simultaneously across multiple sectors—such as sudden regulatory shifts in fintech access, changes in platform data tracking rules, or rapid shifts in consumer online behaviours.

This dimension does not involve unstructured data collection. Instead, it consists of organised internal routines that actively track weak environmental signals, scan alternative industries, and filter out noise. This ensures that executive teams can spot structural disruptions long before they become obvious market shocks.

Digital Analytics Intelligence (DAI)

Digital Analytics Intelligence (DAI) is defined as the organisational capability to use analytical outputs, data-driven methods, and platform metrics as inputs for strategic interpretation rather than as a mere technical analytics function (Akter et al., 2016; Mikalef et al., 2020).

DAI is the cognitive processing engine of the firm. It does not denote the software, hardware, databases, algorithms, or code that constitute Data Analytics Capability. Rather, it refers to the organisational human routines through which managers clean, compare, cross-reference, and interpret analytical outputs in relation to strategic questions. In this sense, DAI moves beyond the possession of dashboards or analytics software; it reflects how managers ask relevant questions, compare multiple data sources, and interpret patterns in relation to market realities. For digitally active firms in Nigeria, this may involve linking customer transaction records, mobile payment behaviour, social media engagement, and platform complaints to identify recurring shifts in demand. Thus, DAI provides the analytical discipline required to prevent information abundance from becoming managerial confusion and to convert data-derived patterns into strategic entrepreneurial decision-making.

Opportunity Recognition Intelligence

Once data are transformed into structured insights via DAI, the firm must determine if those insights reveal a commercially viable opportunity. Opportunity Recognition Intelligence is the organisational capacity to frame, extract, and define viable commercial or strategic entrepreneurial options from synthesised digital data (Nambisan, 2017).

This routine requires creative strategic interpretation. For example, by analysing digital transaction failures or localised search volume spikes, an organisation using Opportunity Recognition Intelligence can identify an unserved customer segment and design a specific digital solution to capture that market. The value of this dimension lies in its ability to move the firm from pattern recognition to opportunity framing. Not every digital signal represents a viable commercial prospect; some may reflect temporary noise, isolated complaints, or non-scalable user behaviour. Opportunity Recognition Intelligence therefore enables managers to interpret whether an observed digital pattern signals a real customer pain point, an emerging market niche, or a possible business model extension. It links analytics to entrepreneurial judgement.

Innovation Evaluation Intelligence

A major challenge in innovation research is avoiding construct redundancy. To prevent overlap with the outcome variable (Innovation Capability), this dimension is conceptualised as Innovation Evaluation Intelligence. It is defined as the organisational capability to critically analyse, select, refine, and vet insights to guide the strategic architecture of new products, services, processes, and business models.

This definition focuses entirely on the interpretive and evaluative decision-making phase rather than the physical development or implementation phase. It isolates the cognitive and analytical selection routines that determine whether a proposed project fits the market, maintaining strict discriminant validity against the physical execution of innovations. Innovation Evaluation Intelligence is particularly important because digital environments often produce multiple attractive but competing options. A firm may identify several possible innovations, but limited resources require managers to prioritise those with the strongest strategic fit, scalability, feasibility, and value-creation potential. This dimension therefore acts as a screening mechanism that reduces impulsive experimentation and ensures that innovation choices are disciplined by evidence, organisational capacity, and market relevance.

Adaptive Intelligence

The final dimension, Adaptive Intelligence, is the proactive organisational capacity to continuously reconfigure internal routines, structural assets, operational workflows, and overarching business strategies based on insights generated through digital interpretation (Teece et al., 2016).

Adaptive Intelligence ensures that the firm does not merely generate reports or remain stuck in a loop of endless analysis. Instead, it serves as the operational engine that translates validated insights into strategic adjustments, allowing the enterprise to actively shape its market environment. This dimension closes the intelligence cycle by ensuring that insights trigger changes in routines, resource deployment, partnership choices, product configuration, or customer engagement strategies. In emerging economies, where regulatory shifts, infrastructure failures, and consumer purchasing power can change quickly, such adaptability is essential. Firms with strong Adaptive Intelligence can revise delivery channels, redesign service models, or reallocate digital investments before competitors respond, thereby turning environmental turbulence into a source of strategic renewal.

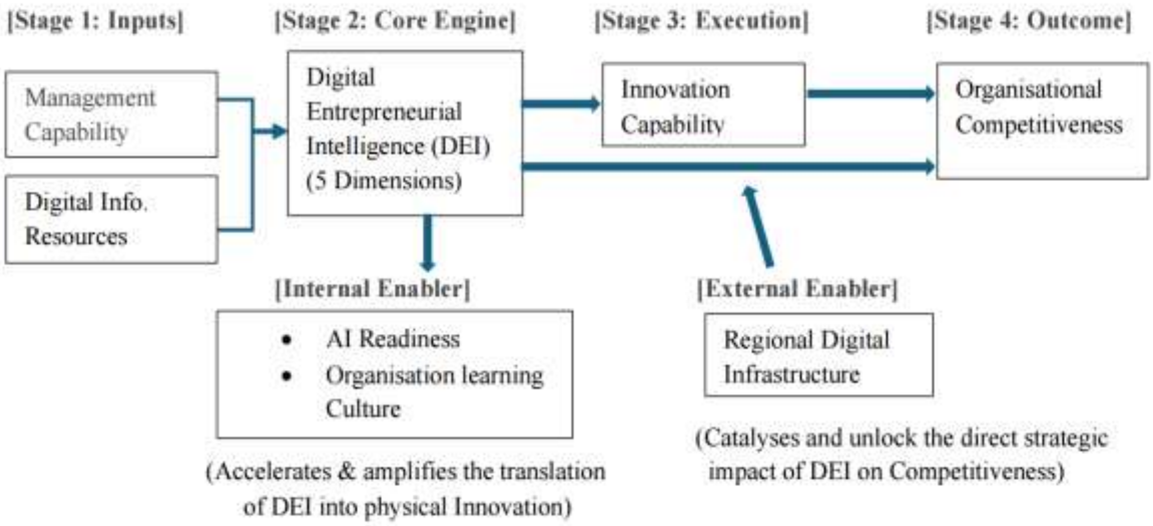
CONCEPTUAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

The proposed conceptual framework operates as an integrated, multi-stage value-transmission system. Rather than modelling foundational antecedents as direct drivers of final firm performance, this framework isolates the sequential, mediated pathways through which raw organisational assets pass to ultimately generate market advantages. The model is structured into three distinct structural phases: the input baseline, the cognitive mediation engine (fuelled by DEI), and the execution-to-performance pipeline.

Crucially, the return on investment from these stages is not static. The framework introduces specific internal and external contingency nodes that act as strategic amplifiers and accelerators of the core engine. Rather than serving as barriers, these moderating factors represent the organisational and environmental infrastructure required to maximise the transmission velocity of Digital Entrepreneurial Intelligence (DEI). Internally, digital capabilities are supercharged and rapidly translated into tangible outputs when supported by computational tools and a culture of agility. Externally, the direct path from intelligence to market success is realised at scale when supported by a stable market architecture.

The precise structural flow, along with the specific inflection points where these internal and external enablers amplify the system's velocity, is visually organised below:

Figure 1: Proposed Conceptual Framework Linking Digital Entrepreneurial Intelligence, Innovation Capability, and Organisational Competitiveness



Drivers and Antecedents of DEI

To build a highly developed Digital Entrepreneurial Intelligence capability, an organisation must possess both structural resources and managerial support. We identify Management Capability and Digital Information Resources as the two primary drivers of DEI.

Management capability reflects the leadership team's strategic competence to orchestrate firm resources, support cross-functional collaboration, and design flexible workflows (Adner & Helfat, 2003). In data-heavy ecosystems, managerial support dictates whether OIPT-aligned information pipelines succeed or succumb to bureaucratic noise (Galbraith, 1974). When leadership teams value data over legacy hierarchies, they create an organisational environment where insights are openly analysed and shared (Warner & Wäger, 2019). Thus:

H1: *Management capability has a direct, positive influence on the development of Digital Entrepreneurial Intelligence.*

Simultaneously, an organisation requires high-quality informational fuel to power its internal intelligence mechanisms. Digital information resources encompass accessible streams of transaction records, online customer engagement logs, platform performance metrics, and digital market updates. Without access to accurate, rich, and timely digital information resources, internal scanning and analytics routines have no inputs to process, which limits the firm's strategic capabilities (Grant, 1996; Wade & Hulland, 2004). Therefore:

H2: *Digital information resources have a direct, positive influence on the development of Digital Entrepreneurial Intelligence.*

Downstream Impacts and Mediating Pathways

Once an organisation establishes a robust DEI capability, it can systematically enhance its strategic performance through two connected downstream pathways. First, DEI strengthens the firm's innovation capability by improving the quality of opportunity interpretation, project selection, and resource prioritisation. Second, it contributes to organisational competitiveness by enabling firms to respond faster and more accurately to changing market conditions. We therefore propose that DEI directly drives Innovation Capability, which subsequently constructs sustainable Organisational Competitiveness.

Innovation capability is defined as a firm's actual capacity to physically construct, launch, and implement novel products, services, operational processes, and business models. DEI acts as the cognitive guide for this execution capability. Organisations with strong DEI do not launch innovations based on guesswork, managerial fashion, or unverified assumptions. Instead, their innovation investments are guided by systematic environmental scanning, digital analytics, opportunity recognition, and rigorous innovation evaluation (Teece, 2007). This improves the likelihood that innovation projects are aligned with real customer needs, feasible market opportunities, and the firm's available resource base. In this sense, DEI does not replace innovation capability; rather, it precedes and strengthens it by ensuring that innovation activity is better informed, more selective, and less exposed to avoidable strategic failure. This ensures higher success rates for new offerings. Thus:

H3: *Digital Entrepreneurial Intelligence has a direct, positive influence on a firm's innovation capability.*

Similarly, DEI directly strengthens overall organisational competitiveness. Competitive advantage in digital markets increasingly depends on how quickly and intelligently firms detect market changes, interpret customer behaviour, and adjust their strategic posture. By enabling firms to spot market shifts early and pivot ahead of rivals, DEI helps enterprises consistently capture premium market shares, reduce customer acquisition costs, improve responsiveness, and build defensive strategic barriers (Barney, 1991). This direct pathway is important because some competitive benefits may emerge before a fully developed innovation is launched. For instance, faster pricing adjustments, improved customer segmentation, better platform positioning, and more accurate resource allocation can all enhance competitiveness through intelligence-led decision-making. Consequently:

H4: *Digital Entrepreneurial Intelligence has a direct, positive influence on overall organisational competitiveness.*

When an organisation successfully deploys its innovation capability to launch unique, high-value products or highly efficient processes, it achieves a sustainable competitive advantage over market rivals who rely on stagnant business models. Innovation capability converts the interpretive benefits of DEI into visible market outputs, including improved products, redesigned services, more efficient processes, and scalable digital business models. This pathway is especially important in emerging economies because firms often compete under resource scarcity; therefore, the ability to innovate efficiently can produce differentiation without requiring excessive capital investment. Innovation capability thus functions as the execution mechanism through which intelligence becomes market performance. Therefore:

H5: *A firm's innovation capability has a direct, positive influence on its organisational competitiveness.*

We further propose that the strategic value of management competence and resource access does not automatically lead to innovation or competitive advantage. Instead, these foundational inputs must be processed through deliberate digital intelligence routines. DEI serves as the vital theoretical bridge that converts general management skills into targeted innovation choices (Nambisan, 2017). It also ensures that raw information assets are transformed into actual market competitiveness through a structured pipeline of scanning, analytics, opportunity framing, evaluation, and adaptation (Yoo et al., 2010). The mediating logic is therefore central to the framework: management capability and information resources create the conditions for intelligence formation, but DEI explains how those conditions are translated into innovation capability. Likewise, innovation capability explains how DEI becomes observable in the marketplace as competitive advantage. This leads to our key mediating hypotheses:

H6: *Digital Entrepreneurial Intelligence significantly mediates the positive relationship between management capability and innovation capability.*

H7: *Innovation capability significantly mediates the positive relationship between Digital Entrepreneurial Intelligence and organisational competitiveness.*

Contextual Boundary Conditions (Moderating Variables)

The translation of digital entrepreneurial insights into tangible innovation, and the subsequent conversion of those insights into market competitiveness, is not automatic; it is bounded by internal organisational characteristics and external environmental conditions. We identify three key moderators: Artificial Intelligence (AI) Readiness, Organisational Learning Culture, and Regional Digital Infrastructure.

Artificial Intelligence readiness refers to the extent to which an organisation has integrated machine learning models, automated algorithms, and advanced automated computing tools into its operational workflows. While human managerial analysis is central to DEI, human cognition can become overwhelmed by big data environments. High AI readiness provides the computational power needed to quickly process massive data streams, automate predictive modelling, and surface hidden patterns (Mikalef et al., 2020). This technological support allows managers to focus on strategic execution, amplifying the positive impact of DEI on innovation. Thus:

H8: *Artificial Intelligence readiness positively moderates the relationship between Digital Entrepreneurial Intelligence and innovation capability, such that the relationship is stronger when AI readiness is high.*

Internally, the firm's cultural context plays a vital role. An organisational learning culture is characterised by an open environment that encourages continuous experimentation, tolerates calculated failures, and values data-driven insights over rigid corporate hierarchies. If a firm possesses high DEI but operates within a highly bureaucratic, risk-averse culture, generated insights will be blocked by internal political resistance. Conversely, an active learning culture ensures that teams can rapidly test and deploy insights without fear of administrative penalties, accelerating the innovation process. Therefore:

H9: *Organisational learning culture positively moderates the relationship between Digital Entrepreneurial Intelligence and innovation capability, such that the relationship is stronger when the learning culture is highly active.*

Finally, external environmental context matters, especially within an emerging economy like Nigeria. Regional digital infrastructure encompasses the availability, stability, and affordability of high-speed broadband networks, cloud computing services, digital payment rails, and reliable electricity grids (World Bank Group, 2019). Even if an enterprise possesses exceptional internal DEI and designs brilliant digital business models, its ability to directly achieve market competitiveness will be limited if its target consumers cannot access stable internet or process digital payments due to network failures (World Bank Group, 2019). Reliable regional infrastructure serves as the external catalyst that allows a firm's digital intelligence to materialise into real market advantages. Consequently:

H10: *Regional digital infrastructure positively moderates the relationship between Digital Entrepreneurial Intelligence and organisational competitiveness, such that the strategic value of DEI is amplified in regions with superior infrastructure.*

PROPOSED FUTURE EMPIRICAL VALIDATION AGENDA

Because this manuscript is presented as a purely conceptual and theory-building contribution, it does not report unfinished, tentative, or premature empirical findings. Instead, this section provides a rigorous future empirical validation agenda that translates the preceding conceptual framework into a testable research programme. This is necessary because DEI is introduced as a novel, higher-order construct; therefore, its theoretical usefulness depends not only on conceptual clarity but also on the possibility of reliable future measurement, empirical testing, and cross-context validation. The roadmap outlined below specifies the psychometric scale development procedures, item-generation logic, validation phases, and statistical parameters required for future researchers to operationalise the five DEI dimensions and examine their relationships with innovation capability and organisational competitiveness. By doing so, the section strengthens the methodological credibility of the paper while preserving its conceptual scope.

Psychometric Scale Development Roadmap

To convert the novel construct of DEI into a fully operationalised, measurable instrument, future empirical research must follow established psychometric scale development guidelines (e.g., Churchill, 1979; Hinkin, 1998; MacKenzie et al., 2011). This process consists of six sequential phases:

[Phase 1: Domain Specification]
↓
[Phase 2: Qualitative Item Generation]
↓
[Phase 3: Content Validity Panel]
↓
[Phase 4: Quantitative Pilot Testing (n=100)]
↓
[Phase 5: Exploratory Factor Analysis (EFA)]
↓
[Phase 6: Confirmatory PLS-SEM Validation (n=450)]

Phase 1: Detailed Domain Specification

Researchers must clearly establish the conceptual boundaries of each sub-dimension of DEI, ensuring there is no behavioural or operational overlap among the indicators.

Phase 2: Qualitative Item Generation

Using the conceptual definitions provided in this paper, researchers should generate an initial pool of at least 6 to 8 survey items per dimension. To ensure contextual relevance, this initial item generation should be informed by qualitative, semi-structured field interviews with digital entrepreneurs and MIS executives operating within Nigeria's digital hubs (such as Lagos and Abuja).

Phase 3: Expert Content Validity Panels

The initial pool of items must be submitted to a blind panel of independent experts, including international MIS professors, entrepreneurship researchers, and active digital business practitioners. These experts will rate each item based on clarity, relevance, and representativeness, filtering out ambiguous or redundant phrasing.

Phase 4: Quantitative Pilot Testing

The refined survey instrument should be administered to a distinct pilot sample of 80 to 100 digitally active enterprises. The resulting data will be used to run preliminary reliability checks, assessing Cronbach's alpha and composite reliability scores.

Phase 5: Exploratory Factor Analysis (EFA)

Using the pilot data, researchers must execute an Exploratory Factor Analysis (typically using principal component analysis with varimax rotation). This step verifies the latent factor structure of the construct. Indicators that exhibit weak factor loadings (<0.70) or cross-loadings across dimensions (>0.40) should be systematically removed to ensure clean unidimensionality.

Phase 6: Confirmatory Field Validation via PLS-SEM

Finally, the optimised instrument must be deployed to a large, representative national sample of enterprises. The resulting dataset will undergo full Confirmatory Factor Analysis (CFA) and structural equation modelling using Partial Least Squares (PLS-SEM) to formally validate the measurement model and test the hypothesised pathways (Hair et al., 2022).

Proposed Illustrative Measurement Scale Items

To jumpstart future empirical work, Table 2 provides a set of preliminary, illustrative survey items designed for a 7-point Likert scale (ranging from 1 = "Strongly Disagree" to 7 = "Strongly Agree"). These items are explicitly structured to capture the operational routines of each dimension while avoiding overlap with adjacent capabilities.

Table 2: Illustrative Measurement Scales for Future Instrument Validation

Latent Construct / Dimension	Item Code	Illustrative Survey Indicator Formulation (7-Point Likert Scale)
Environmental Scanning Intelligence	ESI_1 ESI_2 ESI_3	Our firm systematically utilises digital networks to track emerging business trends. Our internal routines continuously monitor technological disruptions in adjacent industries. We actively filter out market noise to identify early signs of regulatory or consumer shifts.
Digital Analytics Intelligence (DAI)	DAI_1 DAI_2 DAI_3	Our organisation regularly deploys advanced analytical tools to interpret platform data. We systematically cross-reference customer transaction data to uncover core behaviour patterns. Strategic decisions in our firm are consistently backed by data-driven analytics insights.
Opportunity Recognition Intelligence	ORI_1 ORI_2 ORI_3	We frequently identify unserved market niches by analysing digital interaction data. Our firm excels at transforming raw platform analytics into viable new product concepts. We systematically identify customer pain points through structured data monitoring.

Innovation Evaluation Intelligence	IEI_1 IEI_2 IEI_3	Our firm uses clear, data-driven frameworks to assess the viability of new business ideas. We critically evaluate the strategic fit of proposed innovations before allocating development capital. We use structured data patterns to vet and select digital solutions for implementation.
Adaptive Intelligence	ADI_1 ADI_2 ADI_3	Our firm rapidly reconfigures its internal operational workflows when digital signals shift. We can smoothly pivot our business strategy when platform algorithms change. We proactively update our resource configurations to capture newly identified digital trends.

Mathematical and Statistical Sample Size Justification

To ensure methodological rigour in future empirical testing, the sample size must be calculated using exact statistical criteria rather than heuristic approximations. We present two precise mathematical approaches to justify the future empirical target of 450 valid responses.

Verification via the Ten-Times Rule

The traditional ten-times rule in PLS-SEM states that the minimum sample size must be at least 10 times the maximum number of structural paths pointing at any single latent construct within the structural model (Hair et al., 2022). Looking at our conceptual model:

- The DEI construct has 2 structural paths pointing at it (Management Capability and Digital Information Resources).
- The Innovation Capability construct has 5 paths pointing at it (DEI, AI Readiness, Organisational Learning Culture, the DEI x AI Readiness interaction term, and the DEI x Learning Culture interaction term).
- The Organisational Competitiveness construct has 4 paths pointing at it (DEI, Innovation Capability, Regional Digital Infrastructure, and the DEI x Regional Digital Infrastructure interaction term).

Thus, the maximum number of structural paths pointing at any single construct is 5 (at the Innovation Capability level). According to the ten-times rule, the absolute minimum sample size required to mathematically execute the model equations is:

$$\text{Minimum } N = 5 \times 10 = 50 \text{ observations}$$

Verification via Statistical Power Analysis (Cohen, 1992)

Because the ten-times rule is frequently critiqued for lack of statistical precision, we calculate a more rigorous sample requirement using Cohen's (1992) statistical power equations via G*Power software parameters.

To detect subtle structural relationships and interaction effects within an emerging market context, we apply the following highly conservative statistical parameters:

- Effect Size (f^2): 0.15 (representing a standard medium effect size).
- Significance Level (α): 0.05 (the standard error threshold in business research).
- Target Statistical Power ($1 - \beta$): 0.95 (ensuring a 95% probability of detecting actual structural relationships).
- Maximum Number of Predictors: 5 (corresponding to the densest construct node in the structural model).

Using the mathematical distributions for a fixed-effects multiple linear regression F-test, the exact minimum required sample size to guarantee statistical power is:

$$N_{G*Power} = 138 \text{ valid enterprise responses}$$

Justification for the Target Distribution of 450 Responses

While the minimum statistical baseline required to avoid Type II errors is 138 valid responses, we highly recommend a target field distribution that yields 450 valid responses (Hair et al., 2022). This larger sample size is essential due to three distinct factors:

1. Survey Non-Response and Attrition: Empirical field research within emerging economies like Nigeria faces high non-response and incomplete survey rates. Anticipating a conservative 30% to 40% data-cleaning rejection rate due to incomplete entries or unverified business statuses, researchers must distribute at least 750 surveys to secure 450 clean responses.
2. Sub-Group Analysis Resilience: A sample of 450 clean responses allows researchers to split the data for multi-group analysis (MGA) to see if the model holds across different industries (e.g., comparing tech fintech firms with digitalised manufacturing firms) or across different firm sizes (SMEs vs. large enterprises).
3. Covariance Consistency: Larger sample sizes reduce parameter estimate variance in PLS-SEM, ensuring stable path coefficients, reliable standard errors, and strong predictive relevance (Q^2) metrics during journal peer review (Sarstedt et al., 2021).

DISCUSSION AND POLICY IMPLICATIONS

By shifting the scholarly focus from technological asset ownership to internal informational capabilities, this conceptual framework offers a major redirection for digital transformation research. It moves beyond simplistic assumptions that "technology adoption directly yields performance," providing a clear mechanism rooted in OIPT and Dynamic Capabilities: technology adoption merely creates an information pipeline; long-term value generation occurs only when a firm's internal DEI processes and interprets those pipelines to guide strategic choices.

Re-anchoring Emerging-Economy Context: Focus on Nigeria

A notable strength of this conceptual framework lies in its deliberate alignment with the unique socio-technical realities of the Nigerian digital economy. Recent empirical studies in Nigeria emphasise that while basic digital literacy and tool adoption are steadily rising, actual business performance and survival remain precarious due to deep systemic gaps (Adeosun & Shittu, 2022; Olubiyi, 2022).

For instance, research on Nigerian small and medium-sized enterprises (SMEs) indicates that e-commerce, mobile pay-points, and social commerce platforms (such as WhatsApp Business and Instagram) are widely used for basic client interactions, yet very few firms convert these daily transactions into structural strategic insights (Afolayan & Olanrewaju, 2021). The prevalent challenge is not the availability of digital tools, but the severe absence of systematic analytical capability and data-driven administrative routines, a finding that directly validates our conceptualisation of Digital Analytics Intelligence (DAI) and Opportunity Recognition Intelligence as missing organisational pillars in emerging markets.

Furthermore, Nigerian enterprises operate within a landscape characterised by profound institutional voids and severe macro-environmental volatility (Umar et al., 2020). From fluctuating foreign exchange rates and erratic monetary policies to sudden regulatory changes in fintech licensing, local managers face high environmental turbulence. In such a high-velocity environment, static technological resources are easily rendered obsolete.

Instead, sustainability depends heavily on dynamic capabilities (Apulu et al., 2013). Research focusing on South-East Nigerian business clusters confirms that dynamic capabilities, particularly sensing and adaptive routines, are the primary drivers of SME resilience during macroeconomic crises. By introducing DEI, our model details the precise informational mechanisms through which Nigerian managers can perform these sensing and adaptive functions, turning daily operational volatility into structured strategic pivots.

Contextual and National Policy Implications

For managers running enterprises within emerging economies like Nigeria, this framework offers a highly liberating operational insight. Building digital agility does not require immediate, capital-intensive investments in cutting-edge, enterprise-grade AI systems or proprietary software suites. Instead, firms can generate significant strategic value by establishing simple, consistent internal routines to capture, clean, and discuss data signals already flowing through low-cost, highly accessible digital channels—such as WhatsApp transaction logs, Instagram engagement analytics, customer mobile wallet records, and local e-commerce platform trends.

At the macroeconomic and national policy level, this framework redefines how digital development strategies should be constructed. National digital economy strategies should not focus only on physical infrastructure or technology access; they must also strengthen the foundational pillars that enable firms to use digital systems productively, including digital infrastructure, digital platforms, digital financial services, digital entrepreneurship, and digital skills (World Bank Group, 2019).

While these infrastructural investments are necessary to establish basic connectivity, they do not automatically generate economic value if the recipient business ecosystem lacks the internal capabilities to process and interpret the resulting data streams (Suleiman & Akande, 2020). Therefore, national digital economy initiatives must balance physical infrastructure rollouts with extensive, state-sponsored training programmes in data literacy, digital opportunity evaluation, and modern innovation management routines.

While this framework omits macroeconomic outcomes (*Socioeconomic Development*) from the direct structural causal paths to avoid the statistical errors of multi-level aggregation without cross-level data, it acknowledges that a highly competitive, innovation-driven private sector naturally generates broader socioeconomic value.

As competitive firms scale up their operations guided by DEI, they expand regional high-skilled employment opportunities, catalyse localised technology ecosystems, expand the domestic tax base, and introduce vital digital services that build systemic national resilience.

Future Research Scope

Future research streams should focus on validating the proposed DEI instrument across diverse geographic settings (e.g., executing comparative studies between West and East African digital hubs like Lagos and Nairobi) to assess the external generalisability of the framework. Additionally, researchers can explore how the rapid emergence of large language models and generative AI tools might act as automated accelerators or cognitive substitutes for human entrepreneurial judgement within organisational decision funnels.

CONCLUSION

This paper contributes to MIS and digital entrepreneurship scholarship by addressing a long-standing theoretical gap: the limited explanation of how firms transform digital information abundance into entrepreneurial action and sustainable competitive advantage. By conceptualising Digital Entrepreneurial Intelligence (DEI) as a higher-order organisational dynamic capability, the study advances a framework that explains how firms scan turbulent environments, interpret weak digital signals, identify viable opportunities, evaluate innovation options, and adapt strategically in response to changing market conditions.

The proposed framework integrates Dynamic Capabilities Theory, Organisational Information Processing Theory, the Knowledge-Based View, Absorptive Capacity Theory, and Entrepreneurial Cognition into a unified explanatory model. In doing so, it clarifies the informational and cognitive micro-foundations through which sensing, seizing, knowledge conversion, and strategic reconfiguration occur within digitally active firms. This shifts the discussion beyond technological adoption and toward the organisational intelligence routines that determine whether digital resources generate innovation, boost competitiveness, or merely intensify information overload.

The framework is particularly relevant for Nigeria and comparable emerging economies, where digital expansion occurs alongside infrastructural instability, regulatory uncertainty, and resource constraints. In such contexts, access to digital tools alone is insufficient. Competitive advantage depends on the capacity of managers and organisations to interpret digital signals, make evidence-based entrepreneurial choices, and reconfigure resources despite institutional and infrastructural limitations.

The study also offers practical and policy implications. For managers, DEI highlights the need to treat digital information as a strategic resource that must be filtered, interpreted, and translated into action through disciplined organisational routines. For policymakers, the framework suggests that investments in broadband, digital payment systems, incubators, and hardware access should be complemented by capability-building initiatives in data literacy, opportunity evaluation, innovation management, and adaptive decision-making.

Finally, the paper establishes a foundation for future empirical validation. The proposed hypotheses, measurement dimensions, and validation roadmap provide a basis for testing DEI across sectors, firm sizes, and regional digital ecosystems. Future research may further refine the construct, examine its predictive validity, and assess how artificial intelligence and generative technologies reshape entrepreneurial intelligence routines. As digital tools become increasingly ubiquitous and replicable, sustained organisational advantage will depend less on the technologies firms possess and more on the intelligence routines through which they interpret and act upon the digital environment.

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