

Digital resource synergy and competitive advantage: A configurational test of digital resource theory in emerging economies

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ABSTRACT

This study examines the role of digital resource synergy in driving competitive advantage and innovation capability within the framework of Digital Resource Theory (DRT). While the Resource-Based View (RBV) emphasizes the importance of valuable, rare, inimitable, and non-substitutable resources, it remains limited in explaining value creation in digital environments characterized by interconnected and scalable technologies. Addressing this limitation, the study investigates how AI capability, data resources, and cloud infrastructure jointly influence firm performance through digital resource synergy. A quantitative research design was employed using survey data collected from firms operating in digitally active sectors in Nigeria, with a response rate of 78.9%. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that AI capability and cloud infrastructure significantly enhance digital resource synergy, while data resources alone do not. Digital resource synergy, in turn, has a strong positive effect on both competitive advantage and innovation capability and mediates the relationship between digital resources and performance outcomes. Additionally, scalability strengthens the effects of AI and cloud infrastructure on competitive advantage, whereas environmental uncertainty does not significantly moderate the synergy–performance relationship. The study contributes to theory by empirically validating Digital Resource Theory and introducing digital resource synergy as a key mechanism of value creation. Practically, it highlights the importance of integrating digital technologies rather than investing in them in isolation.

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Keywords:

Digital Resource Strategy, Scalability, Recombinability, Environment Uncertainty, Innovation Capability, Competitive Advantage.

Article History:

Received: 04 Apr 2026

Accepted: 20 Jun 2026

Available Online: 30 Jun 2026

1. INTRODUCTION

The global economy is undergoing a profound transformation driven by rapid advancements in digital technologies such as artificial intelligence (AI), big data analytics, and cloud computing. These technologies have fundamentally altered how firms create, deliver, and sustain value, shifting the basis of competitive advantage from tangible assets to digitally embedded resources and capabilities (Brynjolfsson & McAfee, 2014; Verhoef et al., 2021). Unlike traditional resources, digital resources are characterized by scalability, interoperability, and recombination, enabling firms to generate value through integration and continuous reconfiguration across platforms and ecosystems (Yoo et al., 2010; Bharadwaj et al., 2013). In emerging economies such as Nigeria, where infrastructural constraints often limit traditional growth pathways, digital technologies offer a strategic avenue for firms to leapfrog developmental barriers and enhance competitiveness. The Resource-Based View (RBV) has long served as the dominant theoretical lens for explaining firm performance, emphasizing that sustainable competitive advantage arises from valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991; Wernerfelt, 1984). While RBV provides a robust foundation for understanding resource-based advantages, its underlying assumptions of resource stability and firm-specific ownership have been increasingly challenged in the context of digital transformation (Madhani, 2010; Helfat et al., 2023). Digital resources are inherently dynamic, modular, and often shared across ecosystems, making it difficult to explain competitive advantage solely through static resource possession. Consequently, RBV offers limited explanatory power for understanding how firms leverage interconnected digital assets to create value in rapidly evolving environments.

To address these limitations, scholars have advanced complementary perspectives such as Dynamic Capability Theory (DCT), which emphasizes firms' abilities to sense, seize, and reconfigure resources in response to environmental changes (Teece et al., 1997; Teece, 2018), and the Knowledge-Based View (KBV), which highlights knowledge as a critical strategic asset (Grant, 1996). More recently, the Digital Resource View (DRV) has emerged as a context-specific extension of RBV, reconceptualizing resources as digital, scalable, and recombinable entities (Adamu, 2025a; Adamu, 2025b). While these perspectives provide important insights into digital transformation and

resource dynamics, they largely focus on individual resource attributes or capabilities, with limited attention to the interactional and synergistic mechanisms through which digital resources jointly create value. Building on these theoretical advancements, this study introduces and empirically tests Digital Resource Theory (DRT), which posits that competitive advantage in the digital era is not derived from isolated resources but from the synergistic integration and configuration of digital assets. Drawing on the logic of resource recombination and ecosystem-based value creation (Amit & Han, 2017; Adner, 2017; Jacobides et al., 2018), DRT emphasizes that AI capability, data resources, and cloud infrastructure interact to produce outcomes that exceed the sum of their individual contributions. This perspective aligns with emerging evidence that value creation in digital contexts is inherently combinatorial, driven by the integration of multiple interdependent resources within complex technological and organizational systems (Ferreira et al., 2025; Tan et al., 2024).

Despite the enduring relevance of the Resource-Based View (RBV) in explaining firm performance, its applicability in the digital era has become increasingly constrained. RBV primarily focuses on the possession of valuable, rare, inimitable, and non-substitutable resources as the basis of competitive advantage (Barney, 1991; Barney, 2001), yet it assumes relative stability and firm-specific ownership of such resources. In contrast, digital resources such as AI systems, data infrastructures, and cloud platforms are inherently dynamic, scalable, and often distributed across networks and ecosystems (Yoo et al., 2010; Rai et al., 2019). As a result, the traditional RBV framework struggles to explain how firms generate value when competitive advantage depends not only on resource possession but also on the interaction and integration of multiple digital assets (Helfat et al., 2023; Pulka & Tijjani, 2023). Although subsequent theoretical developments, including Dynamic Capability Theory (Teece et al., 1997; Teece, 2018) and the Digital Resource View (Adamu, 2025a; 2025b), attempt to address these limitations by emphasizing adaptability and digital characteristics of resources, they still provide limited empirical insights into the mechanisms through which digital resources combine to create synergistic value. Existing studies have largely examined digital resources in isolation or focused on their direct effects on firm performance, neglecting the possibility that value creation in digital environments is fundamentally combinatorial and configurational (Amit & Han, 2017; Ferreira et al., 2025). Consequently,

there remains a significant gap in understanding how firms orchestrate AI capability, data resources, and cloud infrastructure to achieve superior outcomes. This gap is particularly pronounced in emerging economies such as Nigeria, where firms are increasingly adopting digital technologies to overcome structural and institutional constraints but often lack the strategic capabilities required to effectively integrate these resources. While digital transformation initiatives are expanding across sectors, there is limited empirical evidence on how the synergistic configuration of digital resources influences competitive advantage under varying conditions of scalability and environmental uncertainty (Marzi, 2022; Matsunaga, 2024). Therefore, this study addresses this critical gap by developing and empirically testing Digital Resource Theory (DRT), focusing on digital resource synergy as the central mechanism linking digital assets to competitive advantage in emerging market contexts.

2. LITERATURE REVIEW

The literature on competitive advantage has evolved significantly from traditional resource-based explanations to more dynamic and digitally oriented perspectives. Early strategic management theories emphasized firm-specific resources as the primary drivers of performance; however, the emergence of digital technologies has fundamentally altered the nature, structure, and deployment of such resources. Contemporary research increasingly recognizes that value creation in digital environments is not solely dependent on resource ownership but on the interaction, integration, and configuration of digital assets (Amit & Han, 2017; Ferreira et al., 2025). This section reviews the theoretical foundations underpinning the study and develops a conceptual basis for Digital Resource Theory (DRT), highlighting its relevance in explaining competitive advantage in digitally intensive contexts.

2.1 Theoretical Foundations

2.1.1 Resource-Based View (RBV)

The Resource-Based View (RBV) posits that firms achieve sustained competitive advantage by possessing resources that are valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991; Wernerfelt, 1984). This perspective shifted the focus of strategic analysis from external market positioning to internal firm resources, emphasizing that heterogeneous resource endowments are central to explaining differences in firm performance. Subsequent extensions have further refined RBV by incorporating value creation mechanisms, organizational processes, and the role of resource orchestration in shaping competitive outcomes (Barney & Arikan, 2005; Barney et al., 2021). The framework's enduring influence is also reflected in contemporary reviews that position RBV as a central and evolving pillar of strategic management theory (Kraaijenbrink et al., 2010; Roos, 2021; Kero & Bogale, 2023; Sugiarno & Novita, 2022). However, RBV has been widely criticized for its static orientation and limited applicability in dynamic and technology-driven environments (Madhani, 2010; Helfat et al., 2023; El Shafeey & Trott, 2014). In particular, RBV assumes that resources are relatively stable, scarce, and firm-specific, whereas digital resources are fluid, scalable, and frequently embedded within broader technological and ecosystem structures. Consequently, RBV provides limited insight into how firms generate value through resource interaction, recombination, and continuous evolution processes that are central to competition in digitally mediated environments. Recent scholarship further emphasizes that digital transformation and technological change require more flexible and dynamic theoretical explanations beyond traditional resource-based assumptions (Ebert & Duarte, 2018; Gong & Ribiere, 2021; Plekhanov et al., 2023; Iliyas & Barca, 2025).

2.1.2 Dynamic Capability Theory (DCT)

Dynamic Capability Theory (DCT) extends RBV by focusing on firms' abilities to integrate, build, and reconfigure internal and external competencies in response to rapidly changing environments (Teece et al., 1997; Winter, 2003). This perspective emphasizes processes such as sensing opportunities, seizing them, and transforming organizational resources to maintain competitiveness (Teece, 2018). More recent research further highlights the role of microfoundations, managerial cognition, and organizational routines in enabling dynamic capabilities, particularly in digitally transforming environments (Arndt et al., 2022; Kowalski et al., 2025; Kero & Bogale, 2023). While DCT addresses the adaptability limitations of RBV, it primarily focuses on processes of change rather than the structural properties and interaction patterns of resources themselves. In digital environments, where resources are inherently modular, interoperable, and continuously evolving, understanding how resources combine and interact becomes equally important as understanding how they are reconfigured. Consequently, although DCT provides valuable insights into strategic renewal, it does not fully capture the combinatorial and

systemic nature of digital resource value creation (Goumagias et al., 2022; Ferreira et al., 2025).

2.1.3 Knowledge-Based View (KBV)

The Knowledge-Based View (KBV) conceptualizes knowledge as the most strategically significant resource of the firm (Grant, 1996; Foss, 1996). It emphasizes that firms exist because they are more efficient than markets in integrating and applying specialized knowledge. KBV has been particularly influential in explaining innovation, organizational learning, and knowledge integration processes within firms (Foss & Stieglitz, 2012). In the context of digital transformation, knowledge is increasingly embedded within data, algorithms, and digital systems, thereby expanding the scope of KBV. Digital technologies enable continuous knowledge generation, codification, and application beyond traditional organizational boundaries (Gong & Ribiere, 2021; Plekhanov et al., 2023). However, similar to RBV and DCT, KBV largely treats knowledge as an independent resource rather than examining how it interacts with other digital assets such as AI systems, platforms, and cloud infrastructures. Consequently, KBV provides an incomplete explanation of value creation in environments characterized by interconnected, data-driven, and platform-based resource systems (Ferreira et al., 2025; Xing et al., 2025).

2.1.4 Digital Resource View (DRV)

The Digital Resource View (DRV) emerges as a contemporary extension of RBV, specifically designed to address the unique characteristics of digital resources. DRV reconceptualizes resources as scalable, recombinable, and embedded within digital infrastructures, emphasizing their ability to generate value through integration, reuse, and continuous recombination (Adamu, 2025a; Adamu, 2025b). Unlike traditional resources, digital assets can be replicated at near-zero marginal cost and leveraged across multiple applications, platforms, and contexts. DRV aligns with broader digital strategy literature, which highlights the role of platforms, ecosystems, and network effects in shaping competitive dynamics (Bharadwaj et al., 2013; Parker et al., 2016). It also reflects the increasing importance of data, artificial intelligence, and digital infrastructures as core strategic assets in contemporary organizations (Rai et al., 2019; Perifanis & Kitsios, 2023; Ebert & Duarte, 2018). However, while DRV advances understanding of digital resource characteristics, it remains largely conceptual and does not fully articulate the underlying mechanisms through which digital resources interact, co-evolve, and produce synergistic outcomes. As a result, further theoretical development is required to explain how these interactions systematically generate competitive advantage in digitally mediated environments (Valentowitsch et al., 2024; Willie, 2025).

2.1.5 Toward Digital Resource Theory (DRT)

Building on RBV, DCT, KBV, and DRV, this study advances Digital Resource Theory (DRT) as an integrative framework for explaining competitive advantage in digital environments. DRT posits that value creation arises not from individual resources but from the synergistic configuration and interaction of multiple digital assets, such as AI capability, data resources, and cloud infrastructure. This perspective is grounded in the logic of resource recombination and configurational theory, which emphasizes that novel combinations of resources can create superior value (Amit & Han, 2017). It is further supported by ecosystem-based approaches, which highlight the interdependence of actors and resources within digital systems (Adner, 2017; Jacobides et al., 2018). Recent empirical evidence also suggests that combining digital and non-digital resources enhances firm performance through synergistic effects (Ferreira et al., 2025; Tan et al., 2024). Thus, DRT extends existing theories by introducing digital resource synergy as the central mechanism of competitive advantage, emphasizing that firms must orchestrate and integrate digital assets to achieve superior outcomes.

2.2 Conceptual Review

2.2.1 AI Capability

AI capability refers to a firm's ability to deploy artificial intelligence technologies for automation, prediction, and decision-making. It encompasses technical expertise, data processing capacity, and the integration of AI into business processes (Moderno et al., 2024). AI capability enables firms to enhance efficiency, improve customer experiences, and generate insights from large datasets, thereby contributing to value creation (Perifanis & Kitsios, 2023). However, AI capability alone does not guarantee competitive advantage; its effectiveness depends on its integration with complementary resources such as data and cloud infrastructure. This reinforces the argument that value creation in digital environments is interaction-driven rather than resource-specific.

2.2.2 Data Resources

Data resources represent the availability, quality, and accessibility of structured and unstructured data that firms use for analysis and decision-making. Data serves as the foundational input for AI systems and analytics, making it a critical driver of digital innovation (Rai et al., 2019). The strategic value of data lies not only in its volume but in its ability to be integrated with other resources to generate actionable insights. Consequently, data resources contribute to competitive advantage primarily when combined with analytical capabilities and technological infrastructure.

2.2.3 Cloud Infrastructure

Cloud infrastructure provides scalable and flexible computing resources that enable firms to store, process, and access data efficiently (Marston et al., 2011). It supports the deployment of AI systems and facilitates the integration of digital resources across organizational boundaries. The scalability and interoperability of cloud systems make them essential for enabling digital resource synergy, as they provide the platform through which resources interact and create value.

2.2.4 Digital Resource Synergy

Digital resource synergy refers to the value created through the interaction and integration of multiple digital resources, resulting in outcomes that exceed the sum of their individual effects. This concept is rooted in the theory of resource recombination (Amit & Han, 2017) and supported by recent studies emphasizing the importance of digital integration in value creation (Ferreira et al., 2025; Tan et al., 2024). Digital synergy represents a shift from linear models of resource-performance relationships to a configurational perspective, where competitive advantage emerges from specific combinations of resources.

2.2.5 Competitive Advantage

Competitive advantage refers to a firm's ability to achieve superior performance relative to its competitors through unique resource configurations and capabilities (Barney, 1991). In digital contexts, competitive advantage is increasingly driven by the ability to leverage digital technologies and integrate them effectively within business processes (Verhoef et al., 2021).

2.2.6 Moderating Variables

Scalability: Refers to the ability of digital resources to expand without proportional increases in cost, enhancing their strategic value (Yoo et al., 2010).

Environmental Uncertainty: Reflects the degree of unpredictability in market and technological conditions, influencing how firms leverage resources (Marzi, 2022; Matsunaga, 2024).

2.3 Hypotheses Development

2.3.1 Digital Resources and Digital Resource Synergy

The increasing pervasiveness of digital technologies has shifted strategic emphasis from isolated resource ownership to the integration and orchestration of complementary digital assets. Core digital resources namely AI capability, data resources, and cloud infrastructure perform distinct but interdependent roles within modern organizations. AI capability enhances automation, predictive analytics, and decision-making processes (Moderno et al., 2024; Perifanis & Kitsios, 2023), while data resources provide the essential input for generating insights and training intelligent systems (Rai et al., 2019). Cloud infrastructure, on the other hand, enables scalable storage, processing power, and seamless integration of digital applications across platforms (Marston et al., 2011). From a theoretical standpoint, the resource recombination perspective suggests that value creation arises from the novel combination of resources rather than their independent deployment (Amit & Han, 2017). Similarly, the Digital Resource View (DRV) emphasizes the scalability and recombination of digital assets as key sources of value (Adamu, 2025a; Adamu, 2025b), while ecosystem theory highlights the interdependence of resources within digitally connected systems (Adner, 2017; Jacobides et al., 2018). These perspectives collectively suggest that digital resources function as complementary components of an integrated system, where their interaction produces enhanced outcomes. Empirical evidence further supports this argument, demonstrating that firms achieve superior performance when digital resources are combined rather than deployed in isolation (Ferreira et al., 2025; Tan et al., 2024). Accordingly, digital resource synergy defined as the enhanced value generated through the interaction and integration of digital assets emerges as a critical mechanism linking digital resources to organizational outcomes. Based on this reasoning, the following hypotheses are proposed:

H1a: AI capability positively influences digital resource synergy.

H1b: Data resources positively influence digital resource synergy.

H1c: Cloud infrastructure positively influences digital resource synergy.

2.3.2 Digital Resource Synergy and Competitive Advantage

Traditional strategic management theories, particularly the Resource-Based View (RBV), assert that competitive advantage is derived from valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). However, in digitally intensive environments, the ability to integrate and recombine resources has become more critical than mere resource possession. Digital resource synergy represents a shift toward a combinatorial logic of value creation, where the interaction of multiple digital assets generates outcomes that exceed the sum of their individual contributions. This perspective is central to Digital Resource Theory (DRT), which posits that competitive advantage arises from the synergistic configuration of digital resources rather than isolated capabilities (Adamu, 2025a; Adamu, 2025b; Akram et al., 2023). Supporting this view, digital transformation literature emphasizes that firms derive value by integrating AI, data, and cloud technologies into cohesive and interoperable systems (Nambisan et al., 2019; Verhoef et al., 2021). Empirical studies also indicate that organizations leveraging digital synergy achieve superior performance, innovation, and market positioning (Tan et al., 2024; Ferreira et al., 2025). Therefore, digital resource synergy is expected to act as a direct driver of competitive advantage by enhancing efficiency, innovation, and responsiveness to environmental changes. Accordingly, the following hypothesis is proposed:

H2a: Digital resource synergy positively influences competitive advantage.

H2b: Digital resource synergy positively influences innovation capability.

2.3.3 Mediating Role of Digital Resource Synergy

Although prior studies have examined the direct effects of digital resources on firm performance, emerging evidence suggests that these relationships are often indirect and mediated by interaction mechanisms. The configurational perspective argues that resources influence outcomes through intermediate processes such as integration, alignment, and recombination (Jalil et al., 2018; Amit & Han, 2017). In digital contexts, AI capability, data resources, and cloud infrastructure generate value not independently but through their collective interaction within an integrated system. Digital resource synergy thus serves as a central mediating mechanism linking digital resources to competitive advantage. This is consistent with ecosystem theory, which posits that value creation emerges from coordinated interactions among interdependent resources (Adner, 2017), as well as digital transformation research emphasizing the importance of technological integration (Verhoef et al., 2021). Consequently, the impact of digital resources on competitive advantage is expected to be transmitted through their ability to create synergistic value. To capture the distinct contributions of each digital resource, the mediation effect is decomposed as follows:

H3a: Digital resource synergy mediates the relationship between AI capability and competitive advantage.

H3b: Digital resource synergy mediates the relationship between data resources and competitive advantage.

H3c: Digital resource synergy mediates the relationship between cloud infrastructure and competitive advantage.

2.3.4 Recombinability and Innovation Capability

Recombinability is a defining feature of digital resources, referring to their ability to be reconfigured and integrated into new applications and processes. This characteristic enables firms to continuously innovate by leveraging existing resources in novel ways (Yoo et al., 2010). In digital environments, recombination facilitates experimentation, modularity, and rapid development of new products and services. This relationship is supported by digital innovation literature, which highlights that modular and interoperable systems enable firms to explore new opportunities and enhance innovation outcomes (Nambisan et al., 2019). Additionally, research on digital ecosystems suggests that combining technological resources fosters creativity and accelerates innovation processes (Secundo et al., 2025). Accordingly, recombination is expected to enhance firms' innovation capabilities, leading to the following hypothesis:

H4: Recombinability positively influences innovation capability.

2.3.5 Moderating Role of Scalability

Scalability is a critical characteristic of digital resources, enabling firms to expand operations without proportional increases in cost (Yoo et al., 2010). This property enhances the strategic value of digital assets by allowing firms to leverage them across multiple contexts, markets, and applications. Within the framework of Digital Resource Theory, scalability strengthens the impact of digital resources on competitive advantage by amplifying the benefits of resource integration. From a theoretical perspective, scalability enhances the efficiency and reach of digital resource configurations, thereby

increasing their contribution to performance outcomes. Empirical evidence also suggests that scalable digital infrastructures improve firm competitiveness and operational efficiency (Bharadwaj et al., 2013).

Given that each digital resource contributes differently to competitive advantage, the moderating effect of scalability is decomposed as follows:

H5a: Scalability positively moderates the relationship between AI capability and competitive advantage.

H5b: Scalability positively moderates the relationship between data resources and competitive advantage.

H5c: Scalability positively moderates the relationship between cloud infrastructure and competitive advantage.

2.3.6 Moderating Role of Environmental Uncertainty

Environmental uncertainty refers to the degree of unpredictability in market conditions, technological developments, and competitive dynamics. In highly uncertain environments, firms must rely on flexible and adaptive resource configurations to sustain performance (Marzi, 2022; Matsunaga, 2024). Digital resource synergy provides such flexibility by enabling firms to dynamically integrate and reconfigure digital assets. The moderating role of environmental uncertainty is grounded in Dynamic Capability Theory, which emphasizes adaptability as a key determinant of competitive advantage in turbulent environments (Teece et al., 1997). Under conditions of high uncertainty, the value of digital resource synergy becomes more pronounced, as firms capable of effectively integrating their resources are better positioned to respond to change. Accordingly, the following hypothesis is proposed:

H6: Environmental uncertainty positively moderates the relationship between digital resource synergy and competitive advantage.

2.4 Conceptual Model

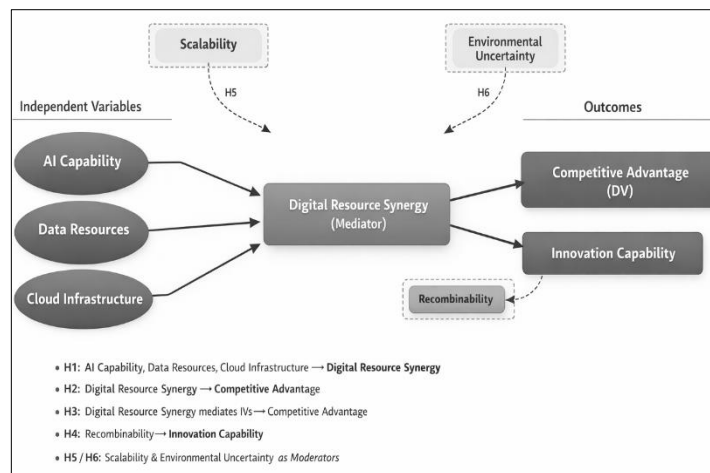


Figure 1. conceptual framework

3. METHODOLOGY

This study adopts a quantitative research design based on a cross-sectional survey approach to empirically test the proposed relationships within the Digital Resource Theory (DRT) framework. The choice of a quantitative method is consistent with theory-testing studies that aim to examine causal relationships among latent constructs (Dost et al., 2018; Hossan et al., 2025). Data are collected from firms operating in digitally active sectors such as SMEs, FinTech, banking, and technology-enabled businesses within Nigeria, reflecting an emerging economy context where digital transformation is rapidly evolving. A structured questionnaire is used as the primary data collection instrument, with measurement items adapted from established studies and refined to fit the study context. The unit of analysis is the firm, with respondents comprising managers, IT specialists, and decision-makers who possess adequate knowledge of their organizations' digital capabilities and strategic operations. The study employs a non-probability purposive sampling technique, targeting firms that actively utilize digital technologies such as AI systems, data analytics, and cloud computing. A sample size ranging between 200 and 400 respondents is considered appropriate, as it satisfies the minimum requirements for Partial Least Squares Structural Equation Modeling (PLS-SEM) and enhances statistical power for hypothesis testing (Hair et al., commonly accepted threshold). Data collection is conducted through both physical and electronic means to maximize response rates. All constructs are measured using a 5-point Likert scale (1 = strongly disagree to 5 = strongly

agree), ensuring consistency and ease of response. To minimize common method bias, respondents are assured of anonymity and confidentiality, and questionnaire items are carefully structured to avoid ambiguity.

Data analysis is conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS, given its suitability for complex models involving mediation and moderation relationships as well as its robustness with relatively small to medium sample sizes. The analysis proceeds in two stages: (1) measurement model assessment, which evaluates reliability and validity using Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE), and discriminant validity (HTMT criterion); and (2) structural model assessment, which examines path coefficients, and coefficient of determination (R^2).

4. RESULT AND DISCUSSION

A total of 380 questionnaires were distributed to respondents across selected SMEs, FinTech firms, banking institutions, and technology-driven organizations in Nigeria, out of which 300 valid responses were retrieved, yielding a high response rate of 78.9%, which is considered adequate for empirical analysis. The demographic distribution shows that 64.0% of respondents were male while 36.0% were female, indicating a male-dominated sample typical of technology-oriented sectors. In terms of age, the majority of respondents fell within the 30–39 years category (42.3%), followed by 40–49 years (26.0%), 20–29 years (18.7%), and 50 years and above (13.0%), suggesting that most participants are within the active and technologically engaged workforce. Regarding educational qualifications, 48.0% held Bachelor's degrees, 32.0% Master's degrees, 12.0% Diplomas, and 8.0% PhD or professional certifications, reflecting a relatively high level of education among respondents. In terms of organizational roles, 46.7% were in middle management, 32.0% in senior management, and 21.3% were junior staff, indicating that the data largely reflects insights from decision-makers. Sectoral distribution reveals that SMEs constituted 40.0% of the sample, followed by FinTech (22.0%), technology firms (20.0%), and banking (18.0%), aligning with the study's focus on digitally active sectors. Additionally, respondents' work experience shows that 38.0% had 6–10 years of experience, 34.0% had 1–5 years, 18.0% had 11–15 years, and 10.0% had above 15 years, suggesting that participants possess sufficient industry exposure to provide reliable insights into digital resource deployment and competitive strategies.

4.1 Assessment of the Models

The assessment of the measurement and structural models was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) in line with established guidelines. The evaluation followed a two-step approach involving the assessment of the measurement model (outer model) and the structural model (inner model). The measurement model was examined for reliability and validity using indicators such as Cronbach's Alpha and Composite Reliability (CR) for internal consistency, with threshold values exceeding 0.70, and Average Variance Extracted (AVE) for convergent validity, with acceptable values above 0.50. Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio, ensuring values below the recommended threshold of 0.85. For the structural model, key criteria such as path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) were evaluated to determine the strength and significance of the hypothesized relationships. Additionally, collinearity issues were assessed using Variance Inflation Factor (VIF) values to ensure the absence of multicollinearity among constructs. These procedures are consistent with the methodological recommendations for PLS-SEM analysis, ensuring the robustness, reliability, and predictive accuracy of the model (Hair et al., 2022; Hair et al., 2024).

The results of the measurement model indicate that all constructs exhibit satisfactory indicator reliability, as evidenced by outer loadings exceeding the recommended threshold of 0.60, with the majority of items surpassing the more stringent benchmark of 0.70. This suggests that the measurement items adequately represent their respective latent constructs and contribute meaningfully to the model. Constructs such as AI Capability, Cloud Infrastructure, Environmental Uncertainty, and Competitive Advantage demonstrate particularly strong loadings, indicating high internal consistency and robustness. Although a few items, including DRS6, DR4, DR5, RC4, and INC5, show relatively moderate loadings, they remain within acceptable limits for exploratory and theory-building research and were retained due to their theoretical relevance and contribution to construct validity. Overall, the pattern of loadings confirms that the measurement model possesses adequate reliability and provides a sound basis for further assessment of convergent and discriminant validity, consistent with established PLS-SEM guidelines (Hair et al., 2022; 2024).

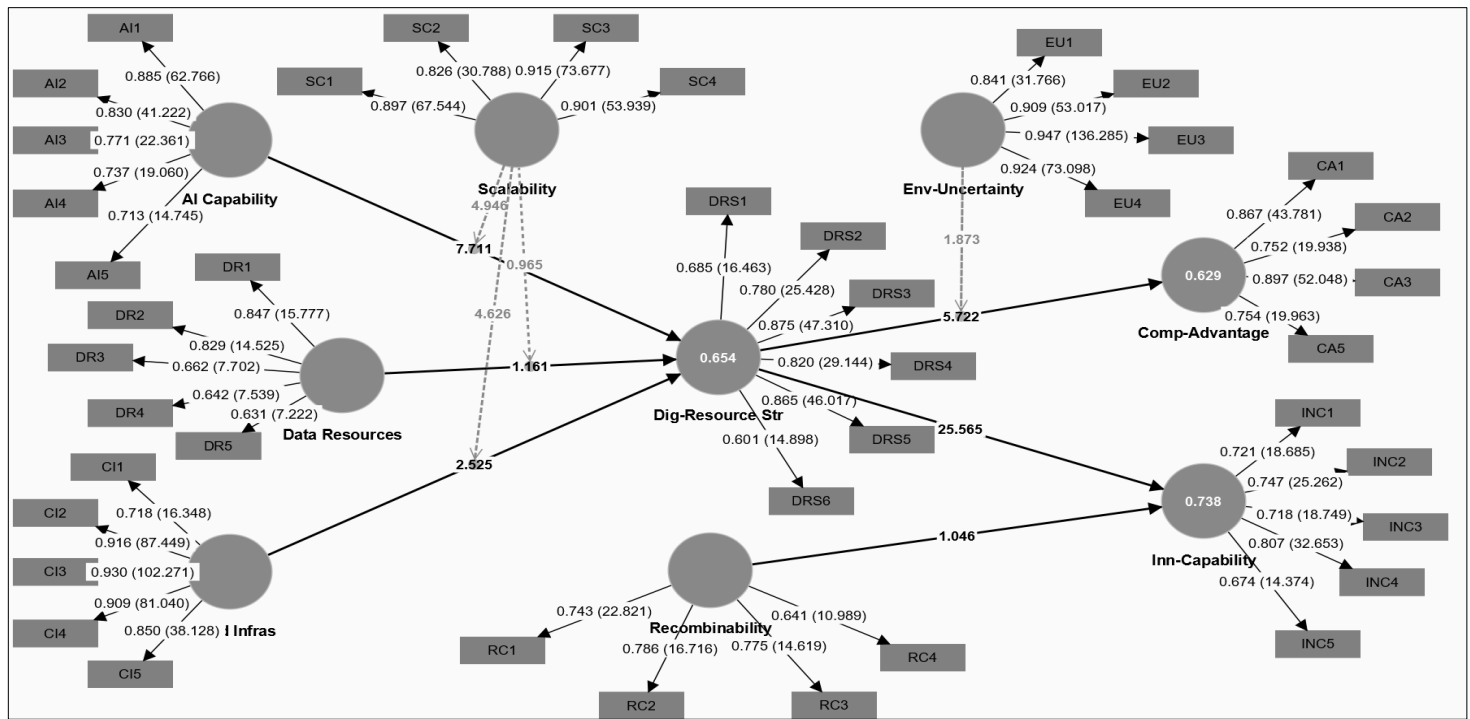


Figure 2. Measurement model

Table 1. Measurement Items and Outer Loadings

Construct	Code	Measurement Item	Loading
AI Capability	AI1	Our firm uses AI technologies to automate key business processes.	0.885
	AI2	Our firm applies AI tools for predictive decision-making.	0.830
	AI3	AI systems in our firm improve operational efficiency.	0.771
	AI4	Our firm has strong technical expertise in AI deployment.	0.737
	AI5	AI is integrated into our core business functions.	0.713
Data Resources	DR1	Our firm has access to large volumes of relevant data.	0.847
	DR2	The data we use is accurate and reliable.	0.829
	DR3	Our firm uses data analytics to support strategic decisions.	0.682
	DR4	Data in our firm is easily accessible for decision-making.	0.642
	DR5	Our firm effectively manages and organizes its data resources.	0.631
Cloud Infrastructure	CI1	Our firm uses cloud platforms for data storage and processing.	0.718
	CI2	Cloud systems in our firm support scalability of operations.	0.916
	CI3	Our firm integrates cloud services across business functions.	0.930
	CI4	Cloud infrastructure improves system flexibility in our firm.	0.909
	CI5	Our firm relies on cloud computing for digital operations.	0.850
Scalability	SC1	Our digital systems can easily scale with business growth.	0.897
	SC2	We can increase operations without significant cost increases.	0.826
	SC3	Our digital platforms accommodate increasing demand efficiently.	0.915
	SC4	Our IT infrastructure supports rapid expansion.	0.901
Digital Resource Synergy	DRS1	AI, data, and cloud systems in our firm work seamlessly together.	0.685
	DRS2	The integration of our digital resources enhances overall performance.	0.780
	DRS3	Our firm effectively combines digital technologies to create value.	0.875
	DRS4	Digital systems in our firm are highly interconnected.	0.820
	DRS5	The joint use of AI, data, and cloud produces better outcomes than using them separately.	0.865
	DRS6	Our firm achieves synergy by integrating multiple digital resources.	0.601
Environmental Uncertainty	EU1	Market conditions in our industry change rapidly.	0.841
	EU2	Technological changes in our industry are unpredictable.	0.909
	EU3	Competitive actions in our industry are uncertain.	0.947
	EU4	Customer preferences are difficult to anticipate.	0.924
Competitive Advantage	CA1	Our firm has a stronger market position than competitors.	0.867
	CA2	Our firm achieves superior performance compared to rivals.	0.752
	CA3	Our firm consistently outperforms competitors.	0.897
	CA4	Our firm maintains sustained competitive advantage.	0.754
	CA5	Our firm frequently introduces new products and services.	0.721
Innovation Capability	INC1	Our firm is highly innovative in its operations.	0.747
	INC2	Our firm adapts quickly to technological changes.	0.718
	INC3	We rapidly develop and implement new ideas.	0.807
	INC4	Innovation is a core strength of our firm.	0.674
	INC5		
Recombinability	RC1	Our firm can easily recombine digital resources for new purposes.	0.743
	RC2	Digital systems in our firm are modular and flexible.	0.786
	RC3	Our firm frequently reuses existing technologies in new ways.	0.775
	RC4	We can quickly integrate new technologies with existing systems.	0.641

Author compilation 2026

Table 2 Internal consistency and convergent validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Capability	0.851	0.882	0.892	0.624
Cloud Infrass	0.916	0.929	0.938	0.754
Comp-Advantage	0.835	0.842	0.891	0.673
Data Resources	0.804	0.851	0.847	0.531
Dig-Resource Str	0.864	0.879	0.9	0.604
Env-Uncertainty	0.927	0.935	0.948	0.821
Inn-Capability	0.788	0.796	0.854	0.54
Recombinability	0.737	0.767	0.827	0.546
Scalability	0.908	0.922	0.936	0.785

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Table 3. Discriminants Validity

	AI Capability	Cloud Infrass	Comp-Advantage	Data Resources	Dig-Resource Str	Env-Uncertainty	Inn-Capability	Recombinability	Scalability
AI Capability	0.79								
Cloud Infrass	0.658	0.868							
Comp-Advantage	0.641	0.633	0.82						
Data Resources	0.477	0.534	0.366	0.728					
Dig-Resource Str	0.695	0.708	0.782	0.411	0.777				
Env-Uncertainty	0.748	0.775	0.725	0.483	0.854	0.906			
Inn-Capability	0.624	0.629	0.859	0.428	0.858	0.711	0.735		
Recombinability	0.818	0.569	0.641	0.41	0.634	0.646	0.572	0.739	
Scalability	0.662	0.797	0.586	0.518	0.687	0.759	0.646	0.546	0.886

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Table 4. Test of Hypotheses

H1-H6	Relationship	Beta	Mean	STDev	T stat	P values	Decision
H1a	AI Capability -> Dig-Resource Str	0.553	0.549	0.072	7.711	0.000	Support
H1b	Data Resources -> Dig-Resource Str	0.052	0.046	0.044	1.161	0.246	Not support
H1c	Cloud Infrass -> Dig-Resource Str	0.173	0.169	0.069	2.525	0.012	Support
H2a	Dig-Resource Str -> Comp-Advantage	0.575	0.577	0.100	5.722	0.000	Support
H2b	Dig-Resource Str -> Inn-Capability	0.829	0.828	0.032	25.565	0.000	Support
H3a	AI Capability -> Dig-Resource Str -> Comp-Advantage	0.318	0.318	0.074	4.310	0.000	Support
H3b	Data Resources -> Dig-Resource Str -> Comp-Advantage	0.030	0.027	0.026	1.123	0.261	Not support
H3c	Cloud Infrass -> Dig-Resource Str -> Comp-Advantage	0.100	0.098	0.043	2.303	0.021	Support
H4	Recombinability -> Inn-Capability	0.047	0.05	0.045	1.046	0.296	Not support
H5a	Scalability x AI Capability -> Comp-Advantage	0.163	0.161	0.046	3.525	0.000	Support
H5b	Scalability x Data Resources -> Comp-Advantage	0.022	0.021	0.023	0.937	0.349	Not support
H5c	Scalability x Cloud Infrass -> Comp-Advantage	0.156	0.155	0.042	3.666	0.000	Support
H6	Env-Uncertainty x Dig-Resource Str -> Comp-Advantage	0.096	0.099	0.051	1.873	0.061	Not support

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The results of internal consistency and convergent validity presented in Table 2 indicate that the measurement model demonstrates satisfactory reliability and validity across all constructs. Specifically, the Cronbach's alpha values range from 0.737 to 0.927, exceeding the recommended threshold of 0.70, thereby confirming acceptable internal consistency. Similarly, the composite reliability values (rho_a and rho_c) for all constructs are above 0.80, indicating strong construct reliability and suggesting that the indicators consistently measure their respective latent variables. In terms of convergent validity, all constructs exhibit Average Variance Extracted (AVE) values above the minimum threshold of 0.50, ranging from 0.531 to 0.821, which confirms that each construct explains more than half of the variance of its indicators. Notably, constructs such as Environmental Uncertainty, Scalability, and Cloud Infrastructure demonstrate particularly high AVE values, reflecting strong indicator convergence. Although constructs like Data Resources and Innovation Capability have relatively lower AVE values, they still meet the acceptable criteria, indicating adequate convergent validity. These results confirm that the measurement model is both reliable and valid, providing a robust foundation for subsequent structural model analysis in line with established PLS-SEM guidelines (Hair et al., 2022; 2024).

The results of the discriminant validity assessment presented below in Table 3, based on the Fornell-Larcker criterion, indicate that the measurement model demonstrates adequate discriminant validity across the constructs. Specifically, the square root of the Average Variance Extracted (AVE), represented by the diagonal elements (e.g., AI Capability = 0.79, Cloud Infrastructure = 0.868, Competitive Advantage = 0.82, Digital Resource Synergy = 0.777, Environmental Uncertainty = 0.906), is greater than the corresponding inter-construct correlations in most cases, confirming that each construct shares more variance with its own indicators than with other constructs. Although some relatively high correlations are observed particularly between Digital Resource Synergy and Environmental Uncertainty (0.854), as well as between Innovation Capability and Competitive Advantage (0.859) the diagonal values remain sufficiently higher or comparable, suggesting that discriminant validity is still acceptable.

These results indicate that the constructs are empirically distinct and measure different conceptual phenomena, thereby supporting the adequacy of the measurement model and justifying the continuation to structural model analysis in line with recommended PLS-SEM criteria (Hair et al., 2022; 2024). The coefficient of determination (R^2) results show that the model explains 62.9% of the variance in Competitive Advantage (CA) and 73.8% of the variance in Innovation Capability (INNC). These values indicate a substantial level of explanatory power, suggesting that the independent and mediating variables meaningfully predict the endogenous constructs. According to established guidelines, these R^2 values reflect strong model performance and good predictive accuracy in explaining firm outcomes (Hair et al., 2022; 2024).

H1a: AI Capability → Digital Resource Synergy (Supported)

The results show that AI capability has a significant and positive effect on digital resource synergy ($\beta = 0.553$, $t = 7.711$, $p < 0.001$), supporting H1a. This indicates that firms with stronger AI capabilities are better able to integrate and coordinate their digital resources, thereby enhancing synergy. The finding aligns with the argument that AI acts as a central integrative mechanism that connects data and infrastructure to generate value. It also supports the theoretical position of Digital Resource Theory (DRT), which emphasizes that intelligent systems facilitate interaction among digital assets, leading to enhanced organizational outcomes.

H1b: Data Resources → Digital Resource Synergy (Not Supported)

The relationship between data resources and digital resource synergy is positive but not statistically significant ($\beta = 0.052$, $t = 1.161$, $p = 0.246$), leading to the rejection of H1b. This suggests that the mere availability or quality of data does not automatically translate into synergy unless it is effectively integrated with other technologies such as AI and cloud systems. The finding implies that data alone is insufficient to drive value creation, reinforcing the notion that digital resources must be actively orchestrated and utilized, rather than simply possessed.

H1c: Cloud Infrastructure → Digital Resource Synergy (Supported)

Cloud infrastructure exhibits a significant positive effect on digital resource synergy ($\beta = 0.173$, $t = 2.525$, $p = 0.012$), supporting H1c. This result

highlights the role of cloud systems as an enabling platform that facilitates the integration and interaction of digital resources. The scalability, flexibility, and interoperability of cloud infrastructure make it a critical backbone for achieving synergy among AI and data resources. This finding is consistent with digital transformation literature emphasizing the importance of cloud-based architectures in supporting integrated digital ecosystems.

H2a: Digital Resource Synergy → Competitive Advantage (Supported)

The findings indicate that digital resource synergy has a strong and significant effect on competitive advantage ($\beta = 0.575$, $t = 5.722$, $p < 0.001$), supporting H2a. This confirms the central proposition of DRT that competitive advantage is derived not from isolated resources but from their synergistic integration. Firms that effectively combine AI, data, and cloud technologies are better positioned to achieve superior performance, differentiation, and market positioning.

H2b: Digital Resource Synergy → Innovation Capability (Supported)

Digital resource synergy also demonstrates a very strong positive effect on innovation capability ($\beta = 0.829$, $t = 25.565$, $p < 0.001$), supporting H2b. This suggests that synergy among digital resources significantly enhances firms' ability to innovate. The magnitude of this relationship indicates that integration and recombination of digital technologies are key drivers of innovation outcomes, reinforcing the idea that digital transformation is inherently innovation-driven.

H3a: AI Capability → Synergy → Competitive Advantage (Supported)

The mediation analysis reveals that digital resource synergy significantly mediates the relationship between AI capability and competitive advantage ($\beta = 0.318$, $t = 4.310$, $p < 0.001$), supporting H3a. This implies that AI contributes to competitive advantage primarily through its ability to enhance synergy among digital resources. Thus, the value of AI is not direct but is realized through its integrative function within the digital ecosystem.

H3b: Data Resources → Synergy → Competitive Advantage (Not Supported)

The mediating effect of digital resource synergy between data resources and competitive advantage is not significant ($\beta = 0.030$, $t = 1.123$, $p = 0.261$), leading to the rejection of H3b. This finding reinforces earlier results that data resources alone do not drive performance unless effectively integrated. It suggests that firms may possess data but lack the necessary capabilities to transform it into strategic value through synergy.

H3c: Cloud Infrastructure → Synergy → Competitive Advantage (Supported)

Digital resource synergy significantly mediates the relationship between cloud infrastructure and competitive advantage ($\beta = 0.100$, $t = 2.303$, $p = 0.021$), supporting H3c. This indicates that cloud infrastructure contributes to competitive advantage indirectly by enabling the integration and coordination of digital resources. The result highlights the foundational role of cloud systems in facilitating digital synergy.

H4: Recombinability → Innovation Capability (Not Supported)

The effect of recombinaibility on innovation capability is positive but not statistically significant ($\beta = 0.047$, $t = 1.046$, $p = 0.296$), leading to the rejection of H4. This suggests that while recombinaibility is theoretically important, it may not directly translate into innovation outcomes without supporting mechanisms such as digital synergy or organizational capabilities. It implies that recombination alone is insufficient unless it is effectively operationalized within the firm.

H5a: Scalability × AI Capability → Competitive Advantage (Supported)

The interaction effect between scalability and AI capability is positive and significant ($\beta = 0.163$, $t = 3.525$, $p < 0.001$), supporting H5a. This indicates that scalability enhances the impact of AI capability on competitive advantage. Firms with scalable digital systems are better able to leverage AI across multiple applications, thereby amplifying its strategic value.

H5b: Scalability × Data Resources → Competitive Advantage (Not Supported)

The moderating effect of scalability on the relationship between data resources and competitive advantage is not significant ($\beta = 0.022$, $t = 0.937$, $p = 0.349$), leading to the rejection of H5b. This suggests that scalability does not strengthen the impact of data resources, further reinforcing the idea that data alone is insufficient for achieving competitive advantage without proper integration and utilization.

H5c: Scalability × Cloud Infrastructure → Competitive Advantage (Supported)

The interaction between scalability and cloud infrastructure is positive and significant ($\beta = 0.156$, $t = 3.666$, $p < 0.001$), supporting H5c. This indicates that scalability enhances the effectiveness of cloud infrastructure in driving competitive advantage. Scalable cloud systems enable firms to efficiently expand operations and leverage digital capabilities across broader contexts.

H6: Environmental Uncertainty × Digital Resource Synergy → Competitive Advantage (Not Supported)

The moderating effect of environmental uncertainty on the relationship between digital resource synergy and competitive advantage is not statistically significant ($\beta = 0.096$, $t = 1.873$, $p = 0.061$), leading to the rejection of H6. Although the relationship is positive and approaches significance, the result suggests that environmental uncertainty does not significantly strengthen the impact of synergy. This may indicate that digital resource synergy is inherently valuable regardless of environmental conditions, or that firms have not fully developed adaptive capabilities to leverage uncertainty.

5. DISCUSSION OF FINDINGS

The findings of this study provide strong empirical support for the central proposition of Digital Resource Theory (DRT), which argues that competitive advantage in the digital era is driven by the synergistic integration of digital resources rather than their isolated possession. The significant effects of AI capability and cloud infrastructure on digital resource synergy (H1a and H1c) confirm that these technologies serve as critical enablers of integration within firms. In contrast, the non-significant effect of data resources (H1b) suggests that data alone does not generate value unless it is effectively processed and integrated with complementary technologies. This finding aligns with prior research emphasizing that the value of digital resources is realized through resource recombination and interaction mechanisms rather than standalone deployment (Amit & Han, 2017; Rai et al., 2019). It also reinforces the argument that digital transformation requires not just resource acquisition but effective orchestration of digital capabilities (Adamu, 2025a; 2025b). Furthermore, the results demonstrate that digital resource synergy has a significant and substantial impact on both competitive advantage and innovation capability (H2a and H2b), highlighting its dual role as a strategic and innovation-driving mechanism. The particularly strong effect on innovation capability suggests that firms that effectively integrate AI, data, and cloud technologies are better positioned to develop new products, services, and processes. This supports the broader digital innovation literature, which emphasizes that innovation in the digital economy is inherently combinatorial and platform-based, relying on the integration of multiple technologies (Nambisan et al., 2019; Verhoef et al., 2021). The findings also align with recent empirical evidence showing that digital synergy enhances firm performance and growth by enabling more efficient and flexible resource utilization (Ferreira et al., 2025; Tan et al., 2024).

The mediation results further strengthen the theoretical contribution of the study by demonstrating that digital resource synergy serves as a key mechanism through which digital resources influence competitive advantage. Specifically, the significant mediation effects for AI capability and cloud infrastructure (H3a and H3c), alongside the non-significant effect for data resources (H3b), suggest that not all digital resources contribute equally to value creation. Instead, their impact depends on their ability to enhance system-wide integration. This finding is consistent with ecosystem theory, which posits that value is created through coordinated interactions among interdependent resources (Adner, 2017; Jacobides et al., 2018). It also supports the view that digital resources must be embedded within a broader technological architecture to generate meaningful outcomes, thereby extending the Resource-Based View beyond static resource ownership toward a more dynamic and interaction-based perspective (Helfat et al., 2023).

Finally, the moderation results provide nuanced insights into the boundary conditions of digital resource value creation. The significant moderating effects of scalability on AI capability and cloud infrastructure (H5a and H5c) indicate that the benefits of these resources are amplified when firms possess scalable systems, consistent with digital strategy literature highlighting scalability as a core feature of digital technologies (Yoo et al., 2010; Bharadwaj et al., 2013). However, the non-significant moderating effects of scalability on data resources (H5b) and environmental uncertainty on digital resource synergy (H6) suggest that contextual factors do not uniformly enhance the impact of all digital resources. These findings imply that while scalability strengthens the exploitation of advanced digital technologies, environmental uncertainty may not necessarily increase the value of synergy unless firms possess strong adaptive capabilities. The results underscore the importance of resource integration, scalability, and strategic alignment in achieving competitive advantage, thereby providing comprehensive empirical validation for Digital Resource Theory in emerging economy contexts.

6. CONCLUSION

This study set out to empirically examine the role of digital resource synergy in shaping competitive advantage and innovation capability within

the framework of Digital Resource Theory (DRT). The findings provide compelling evidence that competitive advantage in the digital era is not driven by the mere possession of digital resources, but by their strategic integration and interaction. Specifically, AI capability and cloud infrastructure were found to significantly enhance digital resource synergy, while data resources alone did not exert a significant effect, highlighting the importance of resource orchestration over resource availability. Furthermore, digital resource synergy emerged as a critical driver of both competitive advantage and innovation capability, confirming its central role as the mechanism through which digital resources create value.

The mediation results reinforce this conclusion by demonstrating that the effects of AI capability and cloud infrastructure on competitive advantage are transmitted through digital resource synergy, thereby validating the core proposition of DRT. In addition, the moderation analysis revealed that scalability strengthens the impact of AI and cloud infrastructure on competitive advantage, while environmental uncertainty does not significantly influence the synergy–performance relationship. These findings suggest that firms achieve superior performance when they effectively integrate scalable digital systems, rather than relying on isolated investments in digital technologies. The study advances strategic management theory by extending the Resource-Based View toward a configurational and interaction-based perspective, providing empirical support for Digital Resource Theory as a relevant framework for understanding competitive advantage in digitally intensive environments, particularly in emerging economies.

6.1 Theoretical Contributions

This study makes a significant theoretical contribution by extending the Resource-Based View (RBV) beyond its traditional emphasis on resource possession toward a more interaction-based and configurational perspective. While RBV posits that competitive advantage stems from valuable, rare, inimitable, and non-substitutable resources (Barney, 1991), this study demonstrates that in digital environments, value is derived primarily from the synergistic integration of digital resources. In doing so, it advances Digital Resource Theory (DRT) by addressing key limitations of RBV, particularly its static orientation, and aligns with recent efforts to renew resource-based thinking in dynamic contexts (Helfat et al., 2023). The study further contributes by empirically validating the Digital Resource View (DRV), showing how AI capability, data resources, and cloud infrastructure interact to produce superior outcomes, thereby establishing digital resource synergy as a central mechanism of value creation and shifting attention from isolated resource effects to combinatorial interactions. Additionally, the study introduces and validates digital resource synergy as a novel construct grounded in resource recombination theory (Amit & Han, 2017) and ecosystem perspectives (Adner, 2017; Jacobides et al., 2018), demonstrating its mediating role in the relationship between digital resources and competitive advantage. Incorporating moderating effects such as scalability, the study adopts a configurational logic, highlighting that the effectiveness of digital resources depends on contextual conditions and integrating linear and non-linear relationships within a unified framework (Fiss, 2011). Finally, the study enhances the generalizability of digital resource-based theories by providing empirical evidence from an emerging economy context and offers a robust foundation for future research, which should extend DRT validation through comparative and longitudinal studies across Global North and Global South contexts, employ configurational methods such as fsQCA to identify multiple pathways to competitive advantage, and incorporate additional boundary conditions including digital normative pressure, digital maturity, organizational culture, and institutional support.

Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this manuscript.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions

All authors contributed significantly to the conception, design, data collection, analysis, and writing of the manuscript. All authors have read and approved the final version of the manuscript.

Informed Consent

Informed consent was obtained from all participants involved in this study prior to data collection.

Use of Generative AI

The authors confirm that generative AI tools were used only for minor language refinement and did not contribute to the intellectual content, analysis, or conclusions of the study.

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