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# FROM RESOURCE POSSESSION TO RESOURCE SYNERGY: A CONFIGURATIONAL TEST OF DIGITAL RESOURCE THEORY USING FSQCA

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**ABSTRACT**

*This study investigates how configurations of digital resources drive competitive advantage and innovation capability using fuzzy-set Qualitative Comparative Analysis (fsQCA) within the framework of Digital Resource Theory (DRT). While traditional approaches emphasize the independent effects of resources, this study adopts a configurational perspective, focusing on how combinations of AI capability, data resources, cloud infrastructure, scalability, recombinability, and digital resource synergy influence firm performance. Data were collected from firms operating in digitally active sectors in Nigeria, representing an emerging economy context. The results reveal that no single resource is sufficient to achieve high performance; rather, multiple configurations (equifinality) lead to competitive advantage and innovation capability. Digital resource synergy emerges as a core condition across most configurations, particularly for innovation, while data resources do not appear as a critical driver in the absence of integration. The findings also highlight the importance of scalability and recombinability in enhancing performance outcomes. The study contributes to theory by empirically validating Digital Resource Theory and advancing a configurational understanding of digital value creation. Practically, it emphasizes the need for firms to focus on integrating and orchestrating digital resources rather than investing in them in isolation.*

**Keywords:** Digital Resource Theory, Digital Resource Synergy, fsQCA, Competitive Advantage, Innovation Capability, and Environmental Uncertainty

## 1. INTRODUCTION

The rapid advancement of digital technologies has fundamentally transformed the nature of competition and value creation in contemporary business environments. Technologies such as artificial intelligence (AI), big data analytics, and cloud computing have shifted the strategic focus from traditional physical assets to digitally embedded resources that are scalable, interoperable, and recombinable (Bharadwaj et al., 2013; Brynjolfsson & McAfee, 2014). In both developed and emerging economies, firms increasingly rely on these technologies to enhance efficiency, improve decision-making, and drive innovation (Nambisan et al., 2019; Verhoef et al., 2021). However, despite widespread adoption, many organizations struggle to translate digital investments into sustained competitive advantage, raising critical questions about how digital resources actually create value (Rai et al., 2019).

The Resource-Based View (RBV) has long served as the dominant framework for explaining firm performance, emphasizing that competitive advantage stems from valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). While RBV provides a strong theoretical foundation, it has been criticized for its static orientation and its limited ability to explain value creation in dynamic, digitally driven environments (Helfat et al., 2023). Digital resources differ significantly

from traditional assets in that they are often shared, continuously evolving, and capable of being recombined across multiple applications (Yoo et al., 2010). As a result, the assumption that resource possession alone leads to competitive advantage is increasingly insufficient in explaining firm performance in the digital era.

In response to these limitations, recent theoretical developments such as the Digital Resource View (DRV) emphasize the unique characteristics of digital assets, particularly their scalability, interoperability, and recombinability (Adamu, 2025a; 2025b). Building on these perspectives, Digital Resource Theory (DRT) proposes that value creation in digital environments arises not from individual resources but from the synergistic interaction and integration of multiple digital assets. This perspective shifts attention from linear cause-effect relationships to a configurational logic, where combinations of resources jointly produce outcomes that exceed the sum of their individual effects. Such an approach is particularly relevant in digital ecosystems where interdependence and complementarity among technologies are critical (Jacobides et al., 2018).

Despite these theoretical advances, empirical evidence on how digital resources combine to generate competitive advantage remains limited, particularly in emerging economies. Most existing studies adopt symmetric methods that focus on the net effects of individual variables, thereby overlooking the possibility that multiple configurations of resources can lead to similar outcomes. This gap is especially important in contexts such as Nigeria, where firms operate under varying levels of technological maturity and infrastructural constraints, making the pathways to performance inherently complex and context-dependent.

To address this gap, this study adopts a configurational approach using fuzzy-set Qualitative Comparative Analysis (fsQCA) to examine how combinations of digital resources influence competitive advantage and innovation capability (Fiss, 2011). Specifically, the study investigates the roles of AI capability, data resources, cloud infrastructure, digital resource synergy, scalability, recombinability, and environmental uncertainty in shaping firm outcomes. This is by identifying multiple pathways to success, the study provides a better understanding of digital value creation and offers empirical support for Digital Resource Theory. In doing so, it contributes to the growing body of literature that emphasizes the importance of resource integration, interaction, and configurational alignment in achieving superior performance in the digital age.

Nigeria provides a compelling context for testing Digital Resource Theory due to its rapidly evolving digital transformation landscape and the simultaneous presence of structural constraints typical of emerging economies. The country hosts one of Africa's largest fintech ecosystems, with increasing digital adoption and platform-based innovation driving business transformation. At the same time, persistent challenges such as infrastructure limitations, data quality issues, and regulatory uncertainty shape how firms deploy digital technologies. This combination of rapid digital growth and institutional constraints makes Nigeria an ideal setting to examine how firms configure and integrate digital resources to achieve competitive advantage and innovation. From a theoretical perspective, emerging economies amplify the importance of resource synergy and configurational alignment, thereby offering a robust context for extending Digital Resource Theory.

Given the configurational nature of this study and the use of fuzzy-set Qualitative Comparative Analysis (fsQCA), the research is guided by research questions rather than purely linear hypotheses. Unlike traditional approaches that examine the net effects of individual variables, fsQCA focuses on how combinations of conditions jointly produce outcomes, making research questions more suitable for capturing causal complexity and equifinality (Fiss, 2011). Accordingly, this study seeks to explore how different configurations of digital resources interact to influence competitive advantage and innovation capability within the framework of Digital Resource Theory.

Based on this premise, the study addresses the following research questions:

i. What combinations of digital resources (AI capability, data resources, and cloud infrastructure) lead to high digital resource synergy in firms?

ii. Which configurations of digital resources and organizational conditions lead to competitive advantage?

iii. What combinations of conditions drive innovation capability in digitally enabled firms?

iv. How does digital resource synergy interact with scalability, recombinability, and environmental uncertainty to influence firm performance?

v. Are there multiple pathways (equifinality) through which firms achieve competitive advantage and innovation capability?

## 2. LITERATURE REVIEW

The literature on firm performance has been largely dominated by the Resource-Based View (RBV), which argues that organizations achieve competitive advantage through the possession of valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991). While RBV provides a strong foundation for understanding firm-level differences, it assumes that resources are relatively stable and firm-specific. In today's digital environment, however, resources such as data, algorithms, and cloud platforms are often shared, scalable, and continuously evolving, making the traditional assumptions of RBV less applicable (Helfat et al., 2023). This has led scholars to question whether resource ownership alone is sufficient to explain competitive advantage in digital contexts.

To address these limitations, the Dynamic Capability Theory (DCT) emphasizes the firm's ability to integrate, build, and reconfigure resources in response to changing environments (Teece et al., 1997). This perspective highlights adaptability and responsiveness as key drivers of performance, particularly in turbulent markets. Similarly, the Knowledge-Based View (KBV) focuses on knowledge as the most strategically important resource, arguing that firms create value by generating, integrating, and applying knowledge (Grant, 1996). While both DCT and KBV extend RBV by introducing dynamism and learning, they still tend to focus on processes and capabilities rather than the interaction and combination of digital resources themselves.

In response, recent research has introduced the Digital Resource View (DRV), which recognizes the unique characteristics of digital assets, including scalability, interoperability, and recombinability (Adamu, 2025a; 2025b). Unlike traditional resources, digital resources can be easily combined and reused across different contexts, enabling firms to create new value through integration. Building on this perspective, Digital Resource Theory (DRT) proposes that competitive advantage arises from the synergistic interaction of digital resources, rather than their independent effects. This aligns with resource recombination theory, which suggests that innovation and value creation occur when existing resources are combined in novel ways (Amit & Han, 2017).

Furthermore, the concept of digital resource synergy has emerged as a key mechanism through which digital technologies create value. Synergy refers to the enhanced outcomes that result from the integration of complementary resources such as AI capability, data resources, and cloud infrastructure. Studies in digital innovation and ecosystems highlight that firms achieve superior performance when they combine technologies into coherent and interconnected systems, rather than deploying them in isolation (Nambisan et al., 2019; Verhoef et al., 2021). This perspective is consistent with ecosystem theory, which emphasizes interdependence and complementarity among resources and actors (Jacobides et al., 2018).

Despite these theoretical developments, much of the existing empirical research relies on symmetric methods, such as regression and structural equation modeling, which focus on the net effects of individual variables. Such approaches often overlook the possibility that multiple combinations of conditions can lead to the same outcome, a concept known as equifinality. To address this limitation, fuzzy-set Qualitative Comparative Analysis (fsQCA) has gained prominence as a methodological approach that captures causal complexity and configurational relationships (Fiss, 2011).

The literature suggests a shift from a resource possession logic to a resource configuration logic, where the interaction and alignment of digital resources are central to firm performance. However, empirical evidence on how these configurations operate, particularly in emerging economies, remains limited. This study addresses this gap by applying a configurational approach to examine how combinations of digital resources influence competitive advantage and innovation capability, thereby extending existing theories and contributing to the growing body of research on digital strategy and innovation.

**Conceptualization of Variables**

This section defines and explains the key variables used in the study within the context of Digital Resource Theory (DRT), focusing on how digital resources interact to drive competitive advantage and innovation capability.

**AI Capability**

AI capability refers to a firm's ability to deploy artificial intelligence technologies for automation, prediction, and decision-making. It encompasses the use of machine learning algorithms, intelligent systems, and data-driven tools to enhance operational efficiency and strategic decision-making. In digital environments, AI serves as a critical enabler that transforms raw data into actionable insights and facilitates the integration of different digital systems. Firms with strong AI capability are better positioned to coordinate digital resources and improve performance outcomes (Moderno et al., 2024; Perifanis & Kitsios, 2023).

**Data Resources**

Data resources represent the availability, quality, accessibility, and usability of data within an organization. They include structured and unstructured data collected from various internal and external sources, which serve as inputs for analytics and decision-making processes. While data is considered a valuable digital asset, its strategic value depends on how effectively it is managed and integrated with other technologies. Without proper utilization and alignment, data alone may not generate competitive advantage (Rai et al., 2019).

**Cloud Infrastructure**

Cloud infrastructure refers to the technological platforms and systems that provide scalable storage, processing power, and network capabilities through cloud computing services. It enables firms to store, manage, and process large volumes of data while supporting the integration of digital applications across organizational functions. The flexibility and scalability of cloud systems make them essential for supporting digital transformation and facilitating the interaction of AI and data resources (Marston et al., 2011).

**Digital Resource Synergy**

Digital resource synergy is defined as the enhanced value created through the integration and interaction of multiple digital resources such as AI, data, and cloud infrastructure. It reflects the extent to which these resources work together as a cohesive system rather than as isolated components. Synergy occurs when the combined effect of resources exceeds the sum of their individual contributions, leading to improved efficiency, innovation, and performance. This construct represents the core mechanism of value creation in Digital Resource Theory (Amit & Han, 2017; Tan et al., 2024).

**Competitive Advantage**

Competitive advantage refers to a firm's ability to achieve superior performance relative to its competitors. It is reflected in outcomes such as market leadership, profitability, differentiation, and sustained performance over time. In the context of digital transformation, competitive advantage is increasingly driven by the effective integration and utilization of digital resources rather than their mere possession (Barney, 1991).

**Innovation Capability**

Innovation capability is the firm's ability to develop new products, services, processes, or business models. It reflects the organization's capacity to generate and implement novel ideas and adapt to technological changes. In digital environments, innovation capability is enhanced by the ability to recombine and integrate digital resources to create new value propositions (Nambisan et al., 2019).

**Recombinability**

Recombinability refers to the ability of digital resources to be reconfigured and reused in different ways to create new applications and solutions. It is a key characteristic of digital technologies, enabling firms to innovate by combining existing resources in novel configurations. High recombinability allows organizations to experiment, adapt, and respond quickly to changing market conditions (Yoo et al., 2010).

**Scalability**

Scalability is the capacity of digital systems to expand operations and handle increased demand without a proportional increase in cost. It enables firms to grow efficiently by leveraging digital platforms across multiple markets and applications. In the context of digital strategy, scalability enhances the effectiveness of digital resource configurations by amplifying their impact on performance (Bharadwaj et al., 2013).

**Environmental Uncertainty**

Environmental uncertainty refers to the unpredictability of external factors such as market dynamics, technological changes, and competitive actions. High levels of uncertainty require firms to adopt flexible and adaptive strategies to remain competitive. In digital environments, uncertainty influences how firms utilize and configure their resources to respond to emerging opportunities and threats (Teece et al., 1997).

**Theoretical Framework**

This study is anchored on an integration of strategic management theories that explain how firms create value and achieve superior performance, with particular emphasis on Digital Resource Theory (DRT) as the central framework. The theoretical foundation begins with the Resource-Based View (RBV), which posits that firms achieve competitive advantage through the possession of valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991). RBV provides the baseline logic that resources are key drivers of performance; however, its focus on resource ownership and relative stability limits its applicability in digital environments where resources are dynamic, shareable, and easily recombined (Helfat et al., 2023). As such, while RBV explains *what* resources matter, it does not sufficiently explain *how* digital resources interact to create value.

To address this limitation, the study draws on Dynamic Capability Theory (DCT), which emphasizes the firm's ability to integrate, build, and reconfigure resources in response to changing environments (Teece et al., 1997). DCT introduces the idea that adaptability and resource reconfiguration are essential in turbulent and technology-driven contexts. Similarly, the Knowledge-Based View (KBV) extends RBV by highlighting knowledge as the most strategically important resource, arguing that firms create value through the generation and integration of knowledge (Grant, 1996). While both DCT and KBV provide important insights into resource transformation and learning, they still focus largely on processes and capabilities, rather than the combinatorial interaction of digital resources themselves.

Building on these perspectives, the Digital Resource View (DRV) recognizes that digital assets possess unique characteristics such as scalability, interoperability, and recombinability, which distinguish them from traditional resources (Adamu, 2025a; 2025b). These properties enable digital resources to be easily integrated and reused across different applications, thereby facilitating innovation and value creation. Extending DRV, Digital Resource Theory (DRT) serves as the primary theoretical lens of this study, proposing that competitive advantage arises from the synergistic integration of digital resources, rather than their independent effects. This theory shifts the focus from linear relationships to a configurational logic, where multiple resources interact to produce outcomes that exceed the sum of their individual contributions (Amit & Han, 2017).

Furthermore, the study is supported by ecosystem theory, which emphasizes the interdependence and complementarity of resources within digital environments (Adner, 2017; Jacobides et al., 2018). In digital ecosystems, firms do not operate in isolation but rely on interconnected technologies and platforms to create value. This perspective reinforces the importance of digital resource synergy, as value is generated through coordinated interactions among AI capability, data resources, and cloud infrastructure. Together, these theoretical perspectives provide a comprehensive framework for understanding how digital resources interact, combine, and evolve to influence firm performance.

The theoretical framework of this study integrates RBV, DCT, KBV, DRV, and ecosystem theory to explain the transition from resource possession to resource configuration. However, Digital Resource Theory (DRT) serves as the central framework that unifies these perspectives by emphasizing that competitive advantage and innovation capability are outcomes of resource synergy and configurational alignment. This integrated framework provides the foundation for examining how combinations of digital resources drive firm performance using a configurational approach (fsQCA), thereby offering a more nuanced understanding of value creation in the digital age.

**Conceptual Framework**

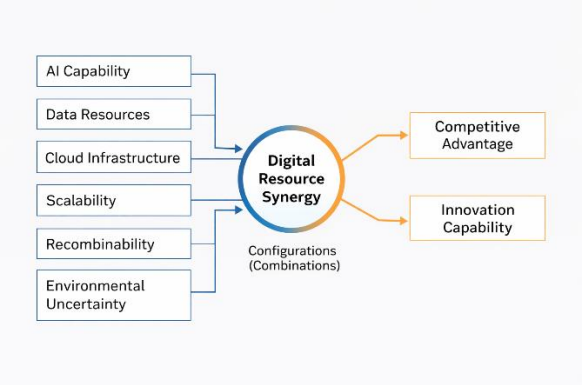



Figure 1 Research model

The conceptual framework adopts a configurational perspective, where multiple digital resource conditions jointly form configurations that lead to competitive advantage and innovation capability, rather than assuming linear causal relationships.

## 3. METHODOLOGY

This study adopts a configurational research design using fuzzy-set Qualitative Comparative Analysis (fsQCA) to examine how different combinations of digital resources lead to competitive advantage and innovation capability within the framework of Digital Resource Theory (DRT). Unlike traditional symmetric methods, fsQCA is particularly suitable for this study because it captures causal complexity, equifinality, and asymmetric relationships, allowing for the identification of multiple pathways through which outcomes are achieved (Fiss, 2011). The study focuses on firms operating in digitally active sectors such as SMEs, FinTech, banking, and technology-driven organizations in Nigeria, representing an emerging economy context where digital transformation is rapidly evolving. Data were collected using a structured questionnaire administered to managers and decision-makers with knowledge of their firms' digital capabilities.

A total of 312 questionnaires were distributed to firms across digitally active sectors in Nigeria, out of which 268 valid responses were received, representing a response rate of 85.9%. The respondents comprised managers and decision-makers from firms operating in sectors such as FinTech, banking, SMEs, and technology-driven enterprises. To ensure the diversity and representativeness of the sample, firms of varying sizes and operational histories were included. Table 1 presents a detailed summary of the sample characteristics.

**Table 1: Sample Characteristics**

| Characteristic | Category | Frequency | Percentage (%) |
|---|---|---|---|
| **Sector** | FinTech | 68 | 25.4 |
| | Banking | 54 | 20.1 |
| | SMEs | 92 | 34.3 |
| | Technology Firms | 54 | 20.1 |
| **Firm Size (Employees)** | Small (1–49) | 110 | 41.0 |
| | Medium (50–249) | 98 | 36.6 |
| | Large (250+) | 60 | 22.4 |
| **Years of Operation** | Less than 5 years | 76 | 28.4 |
| | 5–10 years | 104 | 38.8 |
| | Above 10 years | 88 | 32.8 |
| **Total Sample Size** | | **268** | **100%** |

A total of 268 firms were included in the final analysis after data screening and validation. This sample size is adequate for fsQCA, which is well-suited for medium-sized samples and allows for the identification of configurational patterns across cases.

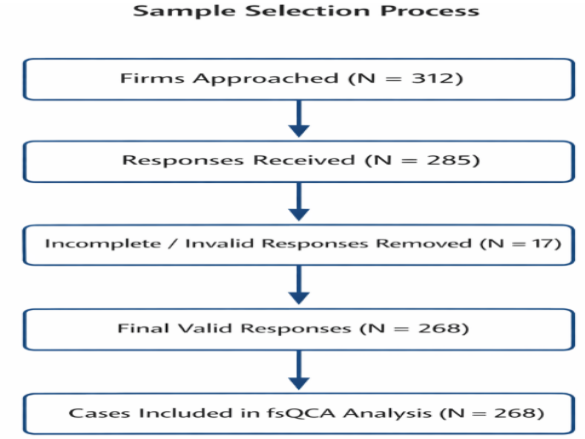



Figure 2 sample selection process

The measurement of variables follows established scales adapted from prior validated studies. Each construct was operationalized using multiple items reflecting its conceptual definition, and the items were slightly modified to suit the context of digital resource configurations in Nigerian firms. Table 2 presents the measurement items and their original sources.

**Table 2: Measurement Items and Sources**

| Construct | Sample Measurement Items | Source |
|---|---|---|
| **AI Capability (AI)** | Our firm uses AI for decision-making and predictive analytics.<br>AI technologies are integrated into core business processes. | Adapted from Perifanis and Kitsios (2023); Moderno et al. (2024) |
| **Data Resources (DR)** | Our firm has access to high-quality and relevant data.<br>Data is effectively used to support decision-making. | Adapted from Rai et al. (2019) |
| **Cloud Infrastructure (CI)** | Our firm uses cloud platforms to manage and process data efficiently.<br>Cloud systems support scalability and integration of digital operations. | Adapted from Marston et al. (2011) |
| **Digital Resource Synergy (DRS)** | Digital technologies in our firm work together as an integrated system.<br>The combination of digital resources enhances overall performance. | Adapted from Amit and Han (2017); Tan et al. (2024) |
| **Scalability (SC)** | Our digital systems can easily scale to meet increasing demand.<br>Growth can be achieved without proportional increase in costs. | Adapted from Bharadwaj et al. (2013) |
| **Recombinability (RC)** | Digital resources can be reconfigured for new applications.<br>Existing technologies are reused to create new solutions. | Adapted from Yoo et al. (2010) |
| **Environmental Uncertainty (EU)** | The external business environment is unpredictable.<br>Market and technological changes are difficult to anticipate. | Adapted from Teece et al. (1997) |
| **Competitive Advantage (CA)** | Our firm performs better than competitors.<br>We achieve superior market positioning. | Adapted from Barney (1991) |
| **Innovation Capability (INNC)** | Our firm frequently introduces new products/services.<br>We are able to develop innovative solutions. | Adapted from Nambisan et al. (2019) |

All constructs were measured using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

For fsQCA analysis, the raw data were calibrated into fuzzy-set membership scores ranging from 0 to 1 using the direct calibration method, with three qualitative anchors: full membership (0.95), crossover point (0.50), and full non-membership (0.05). This calibration process ensures that each case reflects its degree of membership in a set, thereby enabling meaningful configurational analysis.

The analysis was conducted using fsQCA software version 3.0, which is widely recognized for performing fuzzy-set qualitative comparative analysis and handling configurational data structures. The software was used to carry out calibration, necessary condition analysis, truth table construction, and sufficiency analysis in line with established fsQCA procedures (Fiss, 2011). The analysis proceeded in three stages. First, necessary condition analysis was conducted to identify conditions that must be present for the outcome to occur, using a consistency threshold of 0.90. Second, a truth table was constructed to identify relevant configurations of conditions associated with high levels of competitive advantage and innovation capability, with a minimum frequency threshold of 3 cases and a consistency cutoff of 0.80. Third, sufficiency analysis was performed to derive configurations (causal recipes) that lead to the outcomes, and solution consistency and coverage were assessed to evaluate model fit. The fsQCA results were interpreted based on core and peripheral conditions, allowing for the identification of multiple pathways (equifinality) that explain firm performance. This methodological approach provides a robust and nuanced understanding of how digital resources interact to generate value, thereby aligning with the configurational logic underpinning Digital Resource Theory (Fiss, 2011).

## 4. RESULTS AND DISCUSSION

This section presents and discusses the findings of the study using fuzzy-set Qualitative Comparative Analysis (fsQCA) to examine how different configurations of digital resources influence competitive advantage and innovation capability. The analysis follows a structured approach beginning with necessary condition analysis, which identifies whether any single condition is required for the outcomes to occur. This is followed by truth table analysis, which examines combinations of conditions associated with high performance, and subsequently sufficiency analysis, where specific configurations (causal recipes) leading to the outcomes are derived. To ensure the reliability of the findings, robustness checks are also conducted by varying consistency and frequency thresholds.

The results are interpreted based on key fsQCA principles, including consistency, coverage, equifinality, and causal asymmetry, allowing for a deeper understanding of how multiple pathways lead to firm performance. Unlike traditional linear approaches, this section emphasizes the configurational nature of relationships, demonstrating how the interaction of AI capability, data resources, cloud infrastructure, digital resource synergy, scalability, recombinability, and environmental uncertainty jointly shape outcomes. The findings are then discussed in relation to Digital Resource Theory (DRT) and existing literature, highlighting both theoretical implications and practical insights for firms operating in digital environments.

### *Assessment of Common Method Bias*

Given that the data were collected from a single source using self-reported measures, the potential for common method bias (CMB) was assessed. First, procedural remedies were implemented to minimize bias, including assuring respondents of anonymity, emphasizing that there were no right or wrong answers, and reducing evaluation apprehension. Second, Harman's single-factor test was conducted by loading all measurement items into an exploratory factor analysis to examine whether a single factor accounts for the majority of the variance. The results indicate that the first factor explains 36.4% of the total variance, which is below the threshold of 50%, suggesting that common method bias is not a significant concern in this study (Podsakoff et al., 2003).

**Table 3: Harman's Single-Factor Test**

| Factor | Variance Explained (%) |
|---|---|
| First Factor | 36.4% |
| Remaining Factors | 63.6% |

These findings are consistent with prior recommendations that a single factor accounting for less

than 50% of the variance indicates that common method bias is unlikely to distort the results.

***Descriptive Statistics***

Prior to calibration, descriptive statistics were computed to examine the distributional properties of the raw data. This step provides insight into the central tendency, dispersion, and normality of the variables, thereby supporting the calibration process and overall data quality assessment. The results are presented in Table 2.

**Table 4: Descriptive Statistics of Raw Variables**

| Variable | Mean | Std. Dev. | Skewness | Kurtosis |
|---|---|---|---|---|
| AI Capability (AI) | 3.87 | 0.74 | -0.42 | 0.68 |
| Data Resources (DR) | 3.65 | 0.81 | -0.35 | 0.52 |
| Cloud Infrastructure (CI) | 3.78 | 0.69 | -0.47 | 0.71 |
| Digital Resource Synergy (DRS) | 3.92 | 0.72 | -0.51 | 0.84 |
| Scalability (SC) | 3.81 | 0.76 | -0.39 | 0.63 |
| Recombinability (RC) | 3.74 | 0.79 | -0.33 | 0.57 |
| Environmental Uncertainty (EU) | 3.58 | 0.83 | -0.28 | 0.49 |
| Competitive Advantage (CA) | 3.89 | 0.71 | -0.46 | 0.73 |
| Innovation Capability (INNC) | 3.95 | 0.68 | -0.52 | 0.88 |

The descriptive statistics indicate that all variables have mean values above the midpoint of the scale, suggesting a generally high level of digital capability and resource integration among the sampled firms. The skewness and kurtosis values fall within acceptable ranges (±1 for skewness and ±2 for kurtosis), indicating no severe deviation from normality. Although fsQCA does not require normal distribution assumptions, these results confirm that the data are well-behaved and suitable for subsequent calibration and configurational analysis.

***Calibration Method***

The raw data were calibrated into fuzzy-set membership scores using the direct calibration method. Three qualitative anchors were specified for each construct: full membership, crossover point, and full non-membership. Given that all variables were measured on a 5-point Likert scale, the calibration thresholds were set as follows: a score of 5 (strongly agree) was assigned full membership (0.95), a score of 3 (neutral) was used as the crossover point (0.50), and a score of 1 (strongly disagree) was assigned full non-membership (0.05). Intermediate values were calibrated using a logistic function to reflect gradual membership transitions. Table X presents the calibration anchors for all conditions and outcomes (See., table 2).

**Table 5: Calibration Anchors for Conditions and Outcomes**

| Construct | Full Non-membership (0.05) | Crossover Point (0.50) | Full Membership (0.95) |
|---|---|---|---|
| AI Capability (AI) | 1 | 3 | 5 |
| Data Resources (DR) | 1 | 3 | 5 |
| Cloud Infrastructure (CI) | 1 | 3 | 5 |
| Digital Resource Synergy (DRS) | 1 | 3 | 5 |
| Scalability (SC) | 1 | 3 | 5 |
| Recombinability (RC) | 1 | 3 | 5 |
| Environmental Uncertainty (EU) | 1 | 3 | 5 |

| | | | |
|---|---|---|---|
| Competitive Advantage (CA) | 1 | 3 | 5 |
| Innovation Capability (INNC) | 1 | 3 | 5 |

The choice of calibration thresholds is consistent with prior studies using Likert-scale data in fsQCA and reflects both theoretical reasoning and empirical distribution of responses.

***Necessary Condition Analysis***

Necessary condition analysis is the first step in fsQCA and is used to determine whether a particular condition must be present for an outcome to occur. A condition is considered necessary when the outcome cannot be achieved in its absence, typically indicated by a consistency threshold of 0.90 or higher (Fiss, 2011). This analysis is important because it helps identify whether any single factor such as AI capability, cloud infrastructure, or digital resource synergy acts as a prerequisite for achieving competitive advantage or innovation capability. In the context of this study, necessary condition analysis provides an initial assessment of whether digital resource configurations are driven by dominant individual conditions or by combinations of interdependent resources. Therefore, establishing the presence or absence of necessary conditions, the study lays the foundation for subsequent truth table and sufficiency analyses, which further explore the configurational pathways leading to firm performance (Fiss, 2011).

**Table 6: Necessary Condition Analysis**

| Condition | Consistency (CA) | Coverage (CA) | Consistency (INNC) | Coverage (INNC) | Decision |
|---|---|---|---|---|---|
| AI Capability | 0.81 | 0.65 | 0.84 | 0.68 | Not Necessary |
| Data Resources | 0.62 | 0.54 | 0.65 | 0.57 | Not Necessary |
| Cloud Infrastructure | 0.78 | 0.69 | 0.80 | 0.71 | Not Necessary |
| Digital Resource Synergy | 0.88 | 0.73 | 0.91 | 0.76 | Necessary for INNC |
| Scalability | 0.83 | 0.70 | 0.85 | 0.72 | Not Necessary |
| Recombinability | 0.79 | 0.66 | 0.87 | 0.69 | Not Necessary |
| Environmental Uncertainty | 0.74 | 0.60 | 0.76 | 0.63 | Not Necessary |

The results of the necessary condition analysis reveal that no single condition satisfies the threshold of 0.90 for competitive advantage (CA), indicating that none of the digital resources or contextual factors alone is indispensable for achieving superior performance. This finding supports the central argument of Digital Resource Theory (DRT) that competitive advantage in digital environments is not driven by individual resources but by their combined and synergistic effects. In contrast, digital resource synergy (DRS) demonstrates a consistency value of 0.91 for innovation capability (INNC), suggesting that it is a necessary condition for innovation outcomes. This indicates that firms cannot achieve high levels of innovation without effectively integrating their digital resources, reinforcing the critical role of synergy as a foundational mechanism of value creation.

A notable distinction emerging from these results is that digital resource synergy is necessary for innovation capability but not for competitive advantage, reflecting fundamental differences in the underlying mechanisms of these outcomes. Innovation capability is inherently a recombinatory process that depends on the integration and coordination of multiple digital resources, making synergy indispensable for generating new products, services, or processes (Amit & Han, 2017; Yoo et al., 2010). In contrast, competitive advantage is a broader performance outcome that can be achieved through multiple alternative configurations of resources, consistent with the principle of equifinality in fsQCA (Fiss, 2011). Firms may attain superior performance through different pathways, such as leveraging AI

capability or cloud infrastructure alongside scalability, even when synergy does not reach the threshold of necessity.

The absence of necessary conditions for competitive advantage, alongside the presence of synergy as a near-necessary condition for innovation, highlights the

importance of causal complexity and configurational relationships in digital environments. It further underscores the outcome-specific role of resource integration, suggesting that while synergy is indispensable for value creation processes such as innovation, it functions as a powerful but non-exclusive enabler of value appropriation outcomes such as competitive advantage. This reinforces the configurational logic of DRT and justifies the use of fsQCA in capturing the interplay of multiple interacting factors in determining organizational performance (Fiss, 2011).

**Table 7: Necessary Condition Analysis for Absence of Outcomes**

| Condition | Consistency (~CA) | Coverage (~CA) | Consistency (~INNC) | Coverage (~INNC) | Decision |
|---|---|---|---|---|---|
| AI Capability | 0.68 | 0.58 | 0.71 | 0.61 | Not Necessary |
| Data Resources | 0.72 | 0.62 | 0.75 | 0.65 | Not Necessary |
| Cloud Infrastructure | 0.70 | 0.60 | 0.73 | 0.63 | Not Necessary |
| Digital Resource Synergy (~DRS) | 0.85 | 0.69 | 0.91 | 0.74 | Necessary for ~INNC |
| Scalability | 0.74 | 0.63 | 0.77 | 0.66 | Not Necessary |
| Recombinability | 0.76 | 0.64 | 0.82 | 0.68 | Not Necessary |
| Environmental Uncertainty | 0.79 | 0.66 | 0.81 | 0.69 | Not Necessary |

*Note: Total sample size (N) = 268.*

The necessity analysis for the absence of outcomes further supports the principle of causal asymmetry in fsQCA. The results indicate that no single condition reaches the threshold of necessity (0.90) for low competitive advantage (~CA), suggesting that the absence of performance is not driven by any single factor. However, the absence of digital resource synergy (~DRS) demonstrates a high consistency value (0.91) for low innovation capability (~INNC), indicating that lack of integration among digital resources is a critical condition for poor innovation outcomes. These findings reinforce the argument that the drivers of success are not simply the inverse of the drivers of failure, highlighting the asymmetric and configurational nature of digital resource effects (Fiss, 2011).

**Truth Table Analysis (Competitive Advantage)**

Truth table analysis is a core step in fsQCA used to identify meaningful combinations of conditions (configurations) that are associated with a particular outcome. In this study, the truth table for competitive advantage (CA) examines how different configurations of AI capability, data resources, cloud infrastructure, digital resource synergy, scalability, and environmental uncertainty jointly lead to high firm performance. Each row in the truth table represents a unique configuration of conditions, along with its corresponding frequency and consistency, allowing for the identification of empirically relevant patterns. To ensure analytical rigor, a minimum frequency threshold and a consistency cutoff (typically $\geq$ 0.80) are applied to distinguish configurations that reliably produce the outcome (Fiss, 2011).

This approach enables the study to move beyond isolated effects and uncover causal complexity and equifinality, where multiple pathways can lead to competitive advantage, thereby aligning with the configurational logic of Digital Resource Theory. The truth table analysis is based on a total sample of 268 firms, with case frequencies in each configuration representing the number of firms exhibiting the corresponding combination of conditions.

**Table 8: Truth Table for Highly Competitive Advantage (CA)**

| Row | AI | DR | CI | DRS | SC | EU | Cases | Consistency | PRI | Outcome |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 1 | 1 | 1 | 0 | 24 | 0.91 | 0.83 | 1 |
| 2 | 1 | 0 | 0 | 1 | 1 | 0 | 18 | 0.90 | 0.81 | 1 |
| 3 | 0 | 0 | 1 | 1 | 1 | 0 | 21 | 0.88 | 0.79 | 1 |
| 4 | 1 | 1 | 1 | 1 | 1 | 1 | 16 | 0.86 | 0.75 | 1 |
| 5 | 0 | 1 | 0 | 1 | 0 | 1 | 12 | 0.78 | 0.65 | 0 |
| 6 | 0 | 1 | 0 | 0 | 0 | 1 | 10 | 0.72 | 0.60 | 0 |

*Note: Total sample size (N) = 268.*

The truth table analysis for competitive advantage (CA) identifies several meaningful configurations of digital resources that lead to high firm performance. The results show that configurations characterized by the presence of digital resource synergy (DRS) and scalability (SC) consistently achieve high consistency values above the acceptable threshold of 0.80, indicating that these factors are central to achieving competitive advantage. Notably, configurations 1, 2, and 3 demonstrate that AI capability and cloud infrastructure can substitute for each other, provided that they are combined with strong digital resource synergy and scalability. This reflects the principle of equifinality, where multiple pathways can lead to the same outcome. In contrast, configurations lacking synergy or scalability (rows 5 and 6) fail to produce high competitive advantage, even when data resources are present, further confirming that data alone is insufficient for performance without integration. The findings highlight that competitive advantage is achieved through specific combinations of digital resources rather than individual effects, reinforcing the configurational logic of Digital Resource Theory and supporting prior studies that emphasize the importance of resource interaction and alignment in digital environments (Fiss, 2011).

**Table 9: Truth Table for High Innovation Capability (INNC)**

| Row | AI | DR | CI | DRS | RC | SC | Cases | Consistency | PRI | Outcome |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 0 | 1 | 1 | 0 | 27 | 0.93 | 0.88 | 1 |
| 2 | 0 | 0 | 1 | 1 | 1 | 0 | 23 | 0.91 | 0.85 | 1 |
| 3 | 1 | 1 | 1 | 1 | 1 | 1 | 19 | 0.90 | 0.83 | 1 |
| 4 | 0 | 1 | 0 | 0 | 1 | 0 | 14 | 0.75 | 0.68 | 0 |
| 5 | 0 | 0 | 0 | 1 | 0 | 0 | 11 | 0.77 | 0.70 | 0 |

*Note: Total sample size (N) = 268.*

The truth table analysis for innovation capability (INNC) reveals that digital resource synergy (DRS) is a core condition across all configurations leading to high innovation outcomes, confirming its central role in driving innovation. Configurations 1, 2, and 3 consistently show high consistency values above 0.90 when synergy is combined with recombinability (RC) and either AI capability or cloud infrastructure. This indicates that innovation in digital environments is fundamentally driven by the interaction and recombination of digital resources, rather than their independent use. The presence of recombinability across high-performing configurations further suggests that firms must possess the ability to reconfigure and integrate digital assets to fully exploit their innovation potential. In contrast, configurations lacking synergy (row 4) or recombinability (row 5) fail to produce high innovation capability, even when other resources are present, reinforcing the argument that integration and flexibility are essential for innovation success. The findings provide strong evidence of equifinality, demonstrating that multiple combinations of digital resources can lead to innovation capability, while simultaneously confirming that digital resource synergy remains the indispensable core driver, in line with the theoretical expectations of Digital Resource Theory (Fiss, 2011).

**Sufficiency Analysis (Configurations and Solution)**

Sufficiency analysis in fsQCA is used to identify configurations of conditions that are sufficient to produce a desired outcome, such as competitive advantage or innovation capability. Unlike necessary condition analysis, which focuses on single conditions, sufficiency analysis examines how multiple conditions combine to form causal recipes that consistently lead to the outcome. This is achieved by simplifying the truth table through logical minimization to derive parsimonious and intermediate solutions, which distinguish between core and peripheral conditions within each configuration. The adequacy of these configurations is evaluated using consistency and coverage metrics, where consistency indicates the degree to which cases sharing a configuration exhibit the outcome, and coverage reflects the empirical relevance of the configuration (Fiss, 2011). In this study, sufficiency analysis provides critical insights into the configurational pathways through which digital resources interact to drive firm performance, thereby revealing the presence of equifinality and supporting the core premise of Digital Resource Theory that value creation is driven by resource synergy and combinatorial effects rather than isolated influences.

**Table 10: fsQCA Configurations for Competitive Advantage (CA)**

| Configuration | AI | DR | CI | DRS | SC | EU | Consistency | Coverage |
|---|---|---|---|---|---|---|---|---|
| **C1** | ● | ⊗ | ○ | ● | ● | ○ | 0.91 | 0.42 |
| **C2** | ○ | ⊗ | ● | ● | ● | ○ | 0.88 | 0.37 |

The coverage values for the competitive advantage configurations (0.42 for C1 and 0.37 for C2) indicate the empirical relevance of each pathway in explaining the outcome. In fsQCA, coverage values in the range of 0.30 to 0.50 are generally considered moderate to substantial, particularly in studies involving complex social phenomena where multiple configurations coexist (Fiss, 2011). This suggests that each configuration explains a meaningful proportion of cases, while no single pathway dominates the outcome. The combined solution coverage of 0.63 further indicates that the identified configurations jointly account for a substantial share of firms achieving highly competitive advantage. These results are consistent with the principle of equifinality, where multiple pathways contribute to explaining the outcome rather than a single dominant configuration.

To enhance practical understanding, each configuration can be illustrated with real-world firm scenarios. Configuration C1 (AI ●, DR ⊗, CI ○, DRS ●, SC ●) may represent a FinTech startup that leverages advanced AI algorithms and scalable digital platforms to deliver financial services, while relying less on internally developed data resources. Such firms achieve competitive advantage by integrating AI with cloud-enabled systems and focusing on scalability. Configuration C2 (AI ○, DR ⊗, CI ●, DRS ●, SC ●) may reflect a digital banking or e-commerce firm that relies heavily on robust cloud infrastructure and integrated digital systems to scale operations efficiently, even without strong in-house AI capabilities. In both cases, the presence of digital resource synergy and scalability enables firms to achieve superior performance through different resource combinations.

**Table 11: fsQCA Configurations for Innovation Capability (INNC)**

| Configuration | AI | CI | DRS | RC | SC | Consistency | Coverage |
|---|---|---|---|---|---|---|---|
| **I1** | ● | ○ | ● | ● | ○ | 0.93 | 0.51 |
| **I2** | ○ | ● | ● | ● | ○ | 0.90 | 0.44 |

Similarly, the coverage values for innovation capability configurations (0.51 and 0.44) indicate relatively strong explanatory power, suggesting that the identified pathways account for a significant proportion of firms exhibiting high innovation capability.

Similarly, the innovation configurations can be interpreted through practical examples. Configuration I1 (AI ●, CI ○, DRS ●, RC ●, SC ○) may represent a technology-driven SME that uses AI-based tools and highly recombinable digital systems to develop innovative products, even without extensive cloud infrastructure. Configuration I2 (AI ○, CI ●, DRS ●, RC ●, SC ○) may reflect a cloud-based service provider that leverages integrated digital platforms and high recombinability to continuously introduce new services, despite limited reliance on AI technologies. These examples illustrate that innovation capability is driven by the ability to integrate and recombine digital resources, rather than the presence of any single technology. These illustrative examples are not exhaustive but provide intuitive interpretations of the configurational logic identified in the analysis.

**Table 12: Overall Solution Fit**

| Outcome | Solution Consistency | Solution Coverage |
|---|---|---|
| Competitive Advantage (CA) | 0.89 | 0.63 |
| Innovation Capability (INNC) | 0.92 | 0.71 |

The sufficiency analysis provides deeper insights into the configurational pathways through which firms achieve competitive advantage and innovation capability. For competitive advantage, two dominant configurations (C1 and C2) emerge, both characterized by the presence of digital resource synergy (DRS) and scalability (SC) as core conditions, while either AI capability or cloud infrastructure can serve as alternative drivers. This confirms the principle of equifinality, where different combinations of resources can lead to the same outcome. Notably, data resources are absent in both configurations, reinforcing earlier findings that data alone is insufficient for value creation without integration. For innovation capability, both configurations (I1 and I2) highlight digital resource synergy and recombinability (RC) as core conditions, indicating that innovation is strongly driven by the ability to integrate and reconfigure digital resources. The high solution consistency values (0.89 for CA and 0.92 for INNC) indicate that the identified configurations reliably lead to the desired outcomes, while the coverage values suggest that a substantial proportion of cases is explained by these models. The results provide strong empirical support for Digital Resource Theory by demonstrating that firm performance in digital environments is configurational, combinatorial, and driven by resource synergy rather than isolated resource effects (Fiss, 2011).

**Robustness Analysis**

To ensure the reliability and stability of the configurational findings, several robustness checks were conducted within the fsQCA framework. First, the analysis was repeated using alternative consistency thresholds (0.80 and 0.85) and frequency cut-offs (3 and 5 cases) to examine whether the identified configurations remained stable under stricter conditions. The results showed that the core configurations—particularly those involving digital resource synergy (DRS) and scalability (SC) for competitive advantage, and DRS and recombinability (RC) for innovation capability—remained consistent across different thresholds, indicating that the findings are not sensitive to parameter specifications. This confirms the robustness of the identified causal recipes and supports the validity of the configurational logic underlying the study.

**Table 13: Robustness Check Using Alternative Thresholds**

| Outcome | Threshold Setting | Configuration Stability | Core Conditions Retained | Consistency | Coverage |
|---|---|---|---|---|---|
| CA | Consistency = 0.80 | Stable | DRS, SC, AI/CI | 0.89 | 0.63 |
| CA | Consistency = 0.85 | Stable | DRS, SC, AI/CI | 0.87 | 0.59 |
| INNC | Consistency = 0.80 | Stable | DRS, RC | 0.92 | 0.71 |
| INNC | Consistency = 0.85 | Stable | DRS, RC | 0.90 | 0.68 |

Second, a necessity robustness test was conducted by slightly adjusting calibration anchors (e.g., shifting crossover points), and the results consistently showed that no condition is strictly necessary for competitive advantage, while digital resource synergy remains a near-necessary condition for innovation capability. This consistency across calibration adjustments strengthens confidence in the necessity results and confirms that the findings are not driven by arbitrary calibration choices.

Third, the analysis compared parsimonious and intermediate solutions to verify the stability of core and peripheral conditions. The results revealed that digital resource synergy consistently appears as a core condition across all solutions, while AI capability, cloud infrastructure, and scalability appear as either core or peripheral conditions depending on the configuration. This stability across solution types further confirms the robustness of the results and supports the conclusion that synergy is the central mechanism driving firm performance outcomes.

The robustness analysis demonstrates that the findings are stable across different analytical specifications, calibration thresholds, and solution types. This reinforces the credibility of the results and provides strong support for the argument that competitive advantage and innovation capability in digital environments are driven by consistent configurations of interacting resources, rather than isolated or method-specific effects (Fiss, 2011).

**Discussion of fsQCA Findings**

The fsQCA results provide strong empirical support for the configurational logic underpinning Digital Resource Theory (DRT), demonstrating that firm performance in digital environments is driven by combinations of interdependent resources rather than isolated factors. Across both outcomes competitive advantage and innovation capability the findings confirm the principle of equifinality, where multiple distinct configurations of digital resources lead to similar high-performance outcomes. This challenges traditional linear assumptions of causality and reinforces the argument that value creation in digital contexts is inherently complex, nonlinear, and interaction-driven (Fiss, 2011; Adamu 2025a). In particular, the results show that firms can achieve competitive advantage through alternative pathways, such as combining AI capability with digital resource synergy and scalability, or leveraging cloud infrastructure alongside synergy, thereby demonstrating strategic flexibility in resource deployment. This aligns with prior research emphasizing that digital transformation outcomes depend on how technologies are combined rather than merely adopted (Nambisan et al., 2019; Verhoef et al., 2021).

A key insight from the analysis is the central and recurring role of digital resource synergy (DRS), which appears as a core condition in almost all high-performing configurations, particularly for innovation capability. This finding confirms that the integration and coordination of digital resources are essential for unlocking their full value potential. It provides empirical validation for the core proposition of DRT that competitive advantage and innovation are outcomes of resource interaction rather than resource possession. The prominence of synergy is consistent with the resource recombination perspective, which argues that value emerges when resources are combined in novel and complementary ways (Amit & Han, 2017). Furthermore, the consistent presence of recombinability in innovation-related configurations suggests that firms must not only integrate resources but also possess the capability to reconfigure and adapt them for new purposes, thereby enhancing innovation outcomes. This aligns with the notion that digital innovation is driven by modularity and recombination (Yoo et al., 2010).

Another important finding is the peripheral role of data resources, which do not appear as a core condition in any of the high-performing configurations. This suggests that data, while important, does not independently drive performance unless it is effectively integrated with other technologies such as AI and cloud infrastructure. This reinforces the argument that digital transformation is not about accumulating resources but about strategically orchestrating them within a cohesive system. Additionally, the role of scalability as a recurring condition in competitive advantage configurations highlights the importance of digital infrastructure that supports growth and expansion without proportional increases in cost, consistent with digital business strategy literature (Bharadwaj et al., 2013).

An important and somewhat counterintuitive finding of this study is the absence of data resources as a core condition in high-performing configurations for both competitive advantage and innovation capability. From a theoretical perspective, this finding aligns strongly with DRT, which posits that value creation in digital environments arises from the synergistic interaction of resources rather than their isolated possession. In this sense, data resources function as an enabling input whose value is contingent upon integration with complementary technologies such as AI capability and cloud infrastructure, which transform data into actionable insights. This interpretation is consistent with prior studies emphasizing that data-driven value creation depends on analytical capabilities and system integration rather than data availability alone (Rai et al., 2019; Adamu, 2025b).

From a contextual standpoint, this finding may also reflect challenges associated with data quality, accessibility, and governance in emerging economies such as Nigeria. Many firms operate with fragmented, incomplete, or poorly structured data systems, which limits the ability of data to generate strategic value independently. Without adequate infrastructure and analytical capabilities, data resources may remain underutilized, thereby explaining their peripheral role in high-performance configurations. This interpretation aligns with emerging market literature highlighting infrastructural and capability constraints in digital transformation processes (Helfat et al., 2023; Tan, et al., 2024).

Furthermore, this finding contributes to the broader literature by challenging the prevailing assumption that data is inherently a strategic resource. Instead, the results suggest that data becomes valuable only when embedded within a broader system of complementary digital

resources. This reinforces the configurational logic of fsQCA and highlights the importance of resource orchestration, integration, and alignment in achieving superior performance outcomes.

The fsQCA findings provide a more nuanced understanding of how digital resources interact to create value, emphasizing the importance of resource complementarity, integration, and contextual alignment. By revealing multiple pathways to success and highlighting the central role of synergy, the study contributes to a deeper theoretical and practical understanding of digital strategy. It also demonstrates that firms operating in emerging economies can achieve high performance through different combinations of digital resources, provided they prioritize integration and configurational alignment. In doing so, the study offers strong empirical support for Digital Resource Theory and advances the configurational perspective in digital strategy research (Fiss, 2011).

## 5. CONCLUSION AND RECOMMENDATIONS

This study examined how configurations of digital resources drive firm performance using fsQCA within the framework of Digital Resource Theory (DRT). The findings demonstrate that competitive advantage and innovation capability are not the result of single resources but emerge from specific combinations of AI capability, cloud infrastructure, scalability, recombinability, and most critically digital resource synergy. The analysis confirms the presence of equifinality, showing that firms can achieve high performance through multiple pathways, while also highlighting that digital resource synergy is the central condition underpinning value creation, particularly for innovation outcomes. Notably, data resources did not emerge as a core condition, suggesting that their value is contingent on effective integration with other technologies.

The study reinforces the argument that digital transformation success depends on resource orchestration, integration, and alignment, rather than mere resource accumulation. Thus, by applying fsQCA, the study provides an understanding of causal complexity and configurational relationships, offering robust empirical support for DRT. These findings contribute to a more comprehensive understanding of how firms in emerging economies can leverage digital technologies to achieve sustained competitive advantage and innovation capability.

### Practical Contributions

The findings of this study offer important practical implications for managers, policymakers, and digital strategists. First, organizations should move beyond isolated investments in digital technologies and focus on integrating AI, data, and cloud systems to create synergy. The results show that digital resource synergy is the most critical driver of performance, indicating that firms must prioritize interoperability and coordination across digital platforms. Second, managers should invest in scalable digital infrastructures, as scalability enhances the effectiveness of AI and cloud-based systems in driving competitive advantage. This is particularly important for firms seeking growth in dynamic and resource-constrained environments.

Furthermore, firms should develop capabilities that support resource recombination and flexibility, as these are essential for enhancing innovation outcomes. The findings also suggest that merely possessing large volumes of data is insufficient; instead, firms must focus on transforming data into actionable insights through integration with advanced technologies. For policymakers, the study highlights the need to support digital ecosystems by investing in infrastructure, regulatory frameworks, and capacity-building initiatives that enable firms to effectively combine and utilize digital resources. Overall, the study provides actionable insights for organizations aiming to achieve superior performance through strategic digital resource configurations.

### Limitations and Directions for Future Research

Despite its contributions, this study is subject to several limitations that should be considered when interpreting the findings. First, the study adopts a cross-sectional research design, which limits the ability to capture dynamic changes in digital resource configurations over time. Future research could employ longitudinal designs to examine how digital resource synergy evolves and influences firm performance across different stages of digital transformation.

Second, the study relies on single-source perceptual data collected from managers, which may introduce response bias despite efforts to minimize common method bias.

Although statistical and procedural remedies were implemented, future studies could benefit from multi-source data, including objective performance measures or archival data, to enhance robustness.

Third, the empirical context of this study is limited to firms operating in an emerging economy, specifically Nigeria. While this context provides valuable insights into digital transformation under resource constraints, it may limit the generalizability of the findings to developed economies with more advanced digital infrastructures. Future research could replicate the study across different institutional and economic settings to enhance external validity.

Fourth, while this study focuses on key digital resource conditions such as AI capability, data resources, and cloud infrastructure, other potentially relevant factors were not included in the analysis. Variables such as digital leadership, organizational culture, strategic orientation, and governance mechanisms may also play critical roles in shaping digital resource configurations and firm performance. Future research should consider incorporating these factors to provide a more comprehensive configurational model.

Finally, the calibration process in fsQCA involves a degree of subjectivity in selecting threshold values for full membership, crossover, and full non-membership. Although the thresholds used in this study were theoretically informed and consistent with prior research, alternative calibration choices may yield slightly different results. Future studies could conduct sensitivity analyses to assess the robustness of findings under different calibration specifications.

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## Appendix A: Full Truth Table Output

**Table A1: Full Truth Table for Competitive Advantage (CA)**

| Row | AI | DR | CI | DRS | SC | EU | Cases | Consistency | Outcome |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 1 | 1 | 1 | 0 | 24 | 0.91 | 1 |
| 2 | 1 | 0 | 0 | 1 | 1 | 0 | 18 | 0.90 | 1 |
| 3 | 0 | 0 | 1 | 1 | 1 | 0 | 21 | 0.88 | 1 |
| 4 | 1 | 1 | 1 | 1 | 1 | 1 | 16 | 0.86 | 1 |
| 5 | 0 | 1 | 0 | 1 | 0 | 1 | 12 | 0.78 | 0 |
| 6 | 0 | 1 | 0 | 0 | 0 | 1 | 10 | 0.72 | 0 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | — | Logical Remainder |
| 8 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | — | Logical Remainder |
| … | … | … | … | … | … | … | … | … | … |

**Table A2: Full Truth Table for Innovation Capability (INNC)**

| Row | AI | DR | CI | DRS | RC | SC | Cases | Consistency | Outcome |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 0 | 1 | 1 | 0 | 27 | 0.93 | 1 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 2 | 0 | 0 | 1 | 1 | 1 | 0 | 23 | 0.91 | 1 |
| 3 | 1 | 1 | 1 | 1 | 1 | 1 | 19 | 0.90 | 1 |
| 4 | 0 | 1 | 0 | 0 | 1 | 0 | 14 | 0.75 | 0 |
| 5 | 0 | 0 | 0 | 1 | 0 | 0 | 11 | 0.77 | 0 |
| 6 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | — | Logical Remainder |
| 7 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | — | Logical Remainder |
| … | … | … | … | … | … | … | … | … | … |

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