Digital Capability Disclosure, Regulatory Transition, And Corporate Financial Performance of Listed Oil and Gas Firms in Nigeria: An Empirical Calibration

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Abstract—**Digital capability has become a strategic organisational resource with firms increasingly presenting digitalisation as a source of competitive advantage in their annual reports. Yet the financial payoff from digital capability is less settled than this managerial narrative suggests: the information-systems and digital-transformation literatures report inconsistent, context-dependent effects, evidence from African listed firms remains thin, and many studies fail to separate the accumulation of digital capability from its conversion into financial value. This study examines whether digital capability disclosed in annual reports is associated with firm performance among listed Nigerian oil and gas firms, and whether that association changed after the country's post-2020 petroleum-sector regulatory transition. Using a balanced panel of 54 firm-year observations from six firms listed on the Nigerian Exchange (2016–2024), the study builds a Digital Capability Disclosure Index (DCDI) from four separately coded dimensions: Enterprise Digital Systems (EDS), Digital Automation and Intelligent Systems (DAIS), Digital Monitoring and Connectivity (DMC), and Data Analytics and Digital Innovation (DADI). Each dimension is coded from the actual text of annual reports (216 verified coding decisions), not from keyword counts. Firm performance is measured by return on assets (ROA), return on equity (ROE) and Tobin's Q, tested with pooled, firm fixed-effects, and two-way firm-and-year fixed-effects regressions, a regulatory-transition interaction, and dimension-level robustness checks, using HC3 heteroskedasticity-consistent standard errors. Mean DCDI rose from 0.175 (2016–2020) to 0.271 (2021–2024), though not significantly. DCDI showed no statistically robust association with ROA, ROE or Tobin's Q once firm and year differences were controlled for, and the regulatory transition did not significantly moderate the relationship in the preferred panel models; a positive pooled link between DADI and ROA did not survive the addition of firm fixed effects. The study calls this a capability–value realisation gap: digital capability disclosure grew without producing a detectable financial premium. It contributes a disclosure-based, multidimensional measure of digital capability; longitudinal evidence from an under-studied African energy setting; and a clearer conceptual distinction between building digital capability and converting it into measurable performance.**

Index Terms—Digital Capability Disclosure, Digital Transformation, Firm Performance, Dynamic Capabilities, Regulatory Transition, Nigeria Oil and Gas Firms

I. INTRODUCTION

1.1. Background to the Study

Digitalisation has reshaped how firms formulate strategy and organise their activities. Technologies, once largely confined to support functions, now shape core business activities, including operations, information management, customer engagement and business-model development. It therefore goes beyond process automation; it reflects a broader shift in how firms compete, make decisions and respond to changing market conditions. It is often described as organisational change enabled by digital technology, and in its stronger versions, as a reshaping of how firms create and capture value (Bharadwaj et al., 2013; Hess et al., 2016; Vial, 2019; Verhoef et al., 2021). That literature is extensive and still unsettled. Reviews describe digital transformation as technology adoption, strategic renewal, business-model change, organisational capability, or institutional response, and little agrees on which framing is correct (Hausberg et al., 2019; Hanelt et al., 2021; Nadkarni & Prügl, 2021;

Kraus et al., 2022). Even the meaning of "digital transformation" remains widely debated. Several reviews have tried to reconcile its technological, organisational and strategic meanings into one construct, without complete success (Matt et al., 2015; Gong & Ribiere, 2021).

The performance case for digitalisation is straightforward. Integrated systems improve information flow and coordination across the firm. This supports greater automation, reducing manual work and process variation. As operations become more connected, firms also gain better visibility of their assets, while analytics helps turn this information into faster and better-informed decisions. Information-systems research has shown for two decades that IT resources can lift firm performance when paired with the right organisational resources and processes (Bharadwaj, 2000; Melville et al., 2004; Wade & Hulland, 2004; Mithas et al., 2011; Kohli & Grover, 2008), and more recent work reports positive links between digital capability, agility, innovation and performance (Mikalef & Pateli, 2017; Wamba et al., 2017; Mikalef et al., 2020; Li et al., 2022; Homburg & Wielgos, 2022). None of this supports the stronger claim that digitalisation always or readily improves financial performance. IT-capability research has long noted that the capability-performance link is inconsistent across studies. That inconsistency has been traced to measurement choices, context and timing, not to any single "true" effect (Chae et al., 2014).

Recent literature suggests that returns to digital transformation are conditional, not automatic. Digital projects cost money to implement, need complementary human and organisational capability, and can fail outright when strategy, structure, governance and technology are out of step (Warner & Wäger, 2019; Vial, 2019; Sousa-Zomer et al., 2020; Ellström et al., 2022). Grover and Kohli (2013) make a related point about digital strategy specifically: the same visible digital move can create value for one firm and destroy it for another, depending on how competitors and the market respond. Being seen to invest digitally is not the same as benefiting from it. Guo et al. (2023) find that digital transformation can raise productivity while lowering some measures of firm performance, a pattern they call the digitalisation paradox. Zareie et al. (2024) find that organisational capital, governance and information quality shape how much value digital transformation actually creates. Recent systematic reviews describe the digital capability-performance relationship as mixed across countries, industries, firm types and performance measures, rather than uniformly positive (Samsuden et al., 2024; Abakpa & Dvouletý, 2025).

This conditionality matters even more in resource and energy industries, which tend to be asset-heavy, operationally complex, and slower to adopt new digital technology than service industries. Maroufkhani et al.'s (2022) systematic review found that digitalisation in resource and energy industries has focused mostly on operational efficiency and cost reduction, and that oil and gas research is still a small slice of the wider energy-digitalisation literature. Case evidence from European oil and gas firms points the same way. Fernandez-Vidal et al. (2022) show that digital transformation there is a matter of governance, strategic alignment and organisational redesign, not simply buying technology. In Africa, policy and institutional regulation add an additional layer. Nwaiwu (2021) shows that the institutional environment shapes digitalisation and the wider energy transition in Nigeria and South Africa.

Nigeria is therefore a useful setting for this question. Its oil and gas firms operate in an unpredictable macroeconomy and have undergone significant institutional change with the enactment of the Petroleum Industry Act of 2021. The Act was not a digital-transformation law, and we do not treat it as one here. It draws a line in the sand: a point after which changes in disclosed digital capability, and in that capability's link to performance, can be examined against what came before. Institutional theory suggests regulatory environments generally change organisational incentives, reporting practices, and strategic responses (DiMaggio & Powell, 1983; Scott, 2008). Dynamic-capabilities research suggests that a resource's value depends on the firm's ability to sense, seize, and reconfigure in response to changing conditions (Teece et al., 1997; Teece, 2007).

1.2 Statement of the Problem

Three problems motivate this study. First, measuring digital capability remains unsettled. Much of the empirical literature uses digital-word counts, broad adoption indicators, or survey scales. These are useful, but they can flatten distinct capabilities into one label:

an ERP platform is not the same as process automation, industrial telemetry, or predictive analytics. Second, evidence from African listed firms is thin compared with the volume of evidence from China, Europe, and North America. This leaves open the question of whether widely reported digital-performance relationships hold in a different institutional and macroeconomic setting. Third, many studies identify digital adoption without separating capability accumulation from value realisation. That distinction matters, because owning a system says little about how intensively it is used, how good the complementary skills are, or how long benefits take to show up. Digital entrepreneurship research makes a related point at the level of individuals and organisations: capability and its exploitation develop on different timelines (Steininger, 2019).

Set against Nigeria's post-2020 petroleum-sector regulatory transition, these three problems become a concrete empirical question: has digital capability disclosure among listed Nigerian oil and gas firms actually translated into measurable financial performance, or has it simply grown as a matter of disclosure practice without a corresponding performance premium? This question cannot be answered with confidence without a multidimensional, contextually coded measure and a longitudinal panel design. This study addresses that gap.

1.3 Aim and Objectives of the Study

This study aims to examine the association between digital capability disclosure and firm performance among listed oil and gas firms in Nigeria and to determine whether that association changed following the country's post-2020 regulatory transition.

The specific objectives are to:

1. Describe the pattern and composition of digital capability disclosure across the sample firms between 2016 and 2024;
2. Examine the association between the Digital Capability Disclosure Index (DCDI) and firm performance, measured by ROA, ROE and Tobin's Q;
3. Determine whether the post-2020 regulatory transition moderates the association between digital capability disclosure and firm performance; and
4. Assess whether the four digital-capability dimensions (EDS, DAIS, DMC, DADI) relate to firm performance differently from one another.

1.4 Research Questions

1. What is the pattern and composition of digital capability disclosure among listed oil and gas firms in Nigeria between 2016 and 2024?
2. Is digital capability disclosure associated with the firm performance of listed oil and gas firms in Nigeria?
3. Does the post-2020 regulatory transition moderate the association between digital capability disclosure and firm performance?
4. Do the four digital-capability dimensions relate to firm performance differently from one another?

1.5 Research Hypotheses

H_{01}: Digital capability disclosure is positively associated with firm performance.

H_{02}: The association between digital capability disclosure and firm performance is stronger after the post-2020 regulatory transition than before it.

H_{03} (exploratory): The four digital-capability dimensions are not associated with firm performance in the same way; any effect is more likely to appear for higher-order dimensions such as data analytics and digital innovation than for basic infrastructure such as enterprise systems.

1.6 Significance of the Study

Academic: The study contributes a transparent, multidimensional, disclosure-based measure of digital capability that distinguishes enterprise systems, automation, operational connectivity and analytics, instead of collapsing them into a single digital word count. It also adds longitudinal evidence from a setting that remains thin in a literature dominated by China, Europe and North America: Nigerian oil and gas. It also draws a conceptual line between capability possession and capability realisation, connecting the resource-based view, dynamic capabilities, and institutional theory without forcing them into a single deterministic account.

Managerial: For firm management and boards, the study offers evidence-based guidance on how to evaluate digital investment: not by how many systems are acquired or announced, but by whether digital

resources are converted into measurable operational and financial benefit. This has direct value for firms deciding how to prioritise digital investment across enterprise systems, automation, connectivity and analytics.

Policy: For regulators and policymakers, the study cautions against reading rising digital disclosure as evidence that a regulatory transition has produced digital transformation. It points to the kind of disclosure and infrastructure policy that separates technology adoption from realised productivity and makes future digitalisation easier to evaluate.

1.7 Scope of the Study

The study is limited to six oil and gas companies listed on the Nigerian Exchange (Seplat Energy Plc, Oando Plc, MRS Oil Nigeria Plc, TotalEnergies Marketing Nigeria Plc, Conoil Plc, and Eterna Plc), observed over nine years (2016–2024), giving a balanced panel of 54 firm-year observations. Digital capability is measured through disclosure in audited annual reports only, using four dimensions (EDS, DAIS, DMC, DADI) combined into a single Digital Capability Disclosure Index. Firm performance is limited to three measures, ROA, ROE and Tobin's Q, with firm size and leverage as controls and a binary post-2020 regulatory-transition indicator as the moderating variable. The study does not extend to power generation, renewables, or other energy sub-sectors, and it does not use primary survey or interview data.

1.8 Limitations of the Study

The study is constrained principally by its small cross-sectional dimension (six firms), which limits the statistical power available to detect modest effects and restricts the complexity of the panel models that can be credibly estimated. It measures disclosed digital capability rather than the complete stock of technology actually in use, and it cannot fully separate the causal effect of the Petroleum Industry Act from other contemporaneous changes in the operating environment. Chapter Five (Section 5.6) fully discusses these limitations and the design choices made in response, along with suggestions for how future research can address each one.

II. LITERATURE REVIEW

2.1 Conceptual Framework

This study's conceptual framework links an independent variable (digital capability disclosure, measured through four proxies), a dependent variable (firm performance, measured through three proxies), a moderating variable (the post-2020 regulatory transition), and two control variables (firm size and leverage). Figure 2.1 presents the framework.

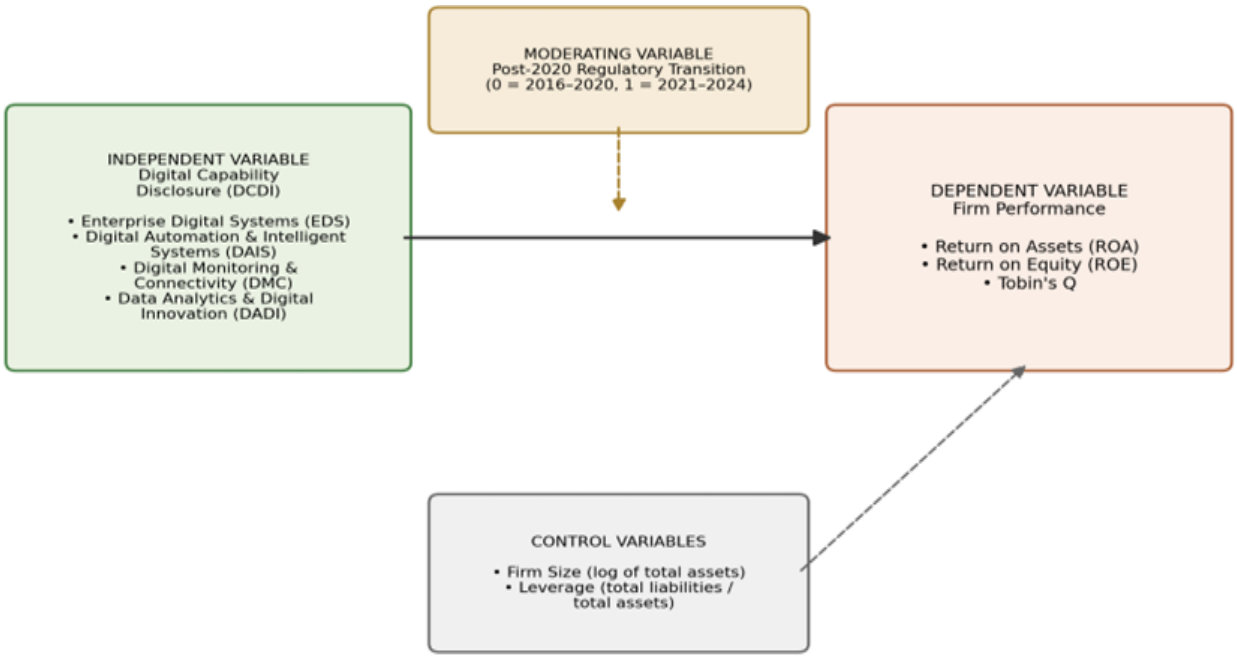


Figure 2.1: Conceptual Framework of the study

2.1.1 Digital Capability Disclosure

This study treats digital capability disclosure as a multidimensional construct: organisational potential that annual reports make visible, not a single undifferentiated "digitalisation" score. It is measured through the Digital Capability Disclosure Index (DCDI), built from four separately coded proxies.

2.1.1.1 Enterprise Digital Systems Disclosure (EDS)

EDS captures enterprise digital systems such as ERP, SAP, integrated business platforms, and substantive firm-specific enterprise applications. These systems link information and workflows across a firm's functions, and their strategic importance predates the current digital-transformation conversation. They can standardise processes and improve coordination, but only if organisational routines change alongside them (Melville et al., 2004; Mithas et al., 2011).

2.1.1.2 Digital Automation and Intelligence Systems Disclosure (DAIS)

DAIS captures process automation, automated workflows, and intelligent systems that reduce manual work. Automation can speed up work, increase consistency, and improve process control. Its value depends on what is being automated and how well it fits the wider operation (Frank et al., 2019; Dalenogare et al., 2018; Tortorella et al., 2021).

2.1.1.3 Digital Monitoring and Connectivity Disclosure (DMC)

DMC captures operational connectivity and monitoring: SCADA, telemetry, sensors, IoT, and remote operational monitoring. This differs from general corporate IT in an important way. It provides visibility into physical processes and distributed assets, and in asset-heavy sectors, it can improve maintenance, safety, and responsiveness (Wamba et al., 2017; Mikalef et al., 2020).

2.1.1.4 Data Analytics and Digital Innovation Disclosure (DADI)

DADI captures business intelligence, advanced analytics, artificial intelligence, machine learning, and substantive data-driven digital innovation. It is treated as a higher-order use of digital resources, because value comes not from collecting data but from turning it into something actionable (Gupta & George, 2016; Wamba et al., 2017; Mikalef et al., 2019).

2.1.2 Firm Performance

Firm performance is operationalised through three complementary proxies, spanning accounting-based profitability and market-based valuation.

2.1.2.1 Return on Assets (ROA)

ROA is profit after tax divided by average total assets, and measures how efficiently a firm converts its asset base into accounting profit. It is the most widely used proxy in the IT-value and digital-capability literature (Bharadwaj, 2000; Mithas et al., 2012), and it suits a capital-intensive sector like oil and gas particularly well: total assets here are dominated by exploration, production and processing infrastructure, so ROA is effectively a test of whether disclosed digital capability corresponds to more accounting profit from that existing asset base, not simply more assets.

2.1.2.2. Return on Equity (ROE)

ROE is profit after tax divided by average shareholders' equity, and measures the accounting return generated on shareholders' capital (Penman, 2013; Damodaran, 2012).

Firm-years with negative equity are excluded from the ROE models because a conventional ROE ratio is difficult to interpret economically under negative equity: dividing a loss by negative equity produces a positive ratio that would misleadingly read as strong performance.

2.1.2.3 Tobin's Q

Tobin's Q is approximated as the sum of the market value of equity and total liabilities, divided by total assets (Tobin, 1969; Chung & Pruitt, 1994). It measures market-based valuation relative to the accounting value of assets and complements the two accounting ratios as a forward-looking measure.

2.1.3 Regulatory Transition

2.1.3.1 Post-2020 Regulatory Transition Indicator

The moderating variable is a binary period indicator, coded 0 for 2016–2020 and 1 for 2021–2024, marking Nigeria's post-Petroleum Industry Act regulatory environment. It is used as a temporal marker of "before" and "after," not as proof that a specific statute caused any observed change (DiMaggio & Powell, 1983; Scott, 2008).

2.1.4 Control Variables

Firm size (the natural log of total assets) and leverage (total liabilities divided by total assets) are included as control variables, since both are well established in the firm-performance literature as persistent, firm-level influences on profitability and valuation that could otherwise confound the association between digital capability disclosure and performance.

2.2 Theoretical Review

2.2.1 Resource-Based View

The resource-based view (Barney, 1991) holds that firms can sustain a competitive advantage through resources that are valuable, rare, difficult to imitate, and non-substitutable. Applied to information technology, Bharadwaj (2000) argued that IT capability is not the same as owning hardware or software. It is the ability to mobilise and deploy IT-based resources alongside a firm's other resources. Wade and Hulland (2004) placed information-systems resources directly within the resource-based view, and Melville et al. (2004) showed that IT creates business value through complementary organisational resources and competitive context, not through spending alone. Nevo and Wade (2010) add that value comes from the interaction between a technology and the non-technical resources it is paired with, not from either alone. That is one reason a single "digital capability" line item can mean very different things across firms. This is the theory's job in the present study: it explains why heterogeneous digital resources might matter for performance.

2.2.2 Dynamic Capabilities Theory

Dynamic capabilities theory (Teece, Pisano, & Shuen, 1997; Teece, 2007) explains why firms differ in their ability to sense, seize, and reconfigure resources under changing conditions, a distinction the resource-based view alone does not draw. Warner and Wäger (2019) identify digital sensing, seizing and transforming routines as the microfoundations of strategic renewal. Sousa-Zomer et al. (2020) treat digital transforming capability as a higher-order capability built from individual and organisational microfoundations. Helfat and Peteraf (2003) show that capabilities have their own lifecycles (founding, development, maturity), so a firm's digital capability at any point reflects where it sits in that lifecycle rather than a fixed endowment. Schilke, Hu and Helfat (2018), in a content-analytic review of the dynamic-capabilities literature, note that the construct works best empirically when studies keep capability possession separate from its exercise. This study draws a similar line between disclosed digital capability and realised financial performance: the theory explains why firms differ in how well they convert digital resources into strategic change and, ultimately, performance.

2.2.3 Institutional Theory

Institutional theory (DiMaggio & Powell, 1983; Scott, 2008) explains why incentives and constraints around organisational practice, including capability development and disclosure, shift over time and across settings in response to coercive, mimetic, and normative pressures. Nwaiwu (2021) shows that policy and regulatory environments shape digitalisation and the wider energy transition in Nigeria and South Africa specifically. This is why the study includes Nigeria's post-2020 regulatory transition as a moderating variable: a changed institutional environment can alter firms' incentives to invest in and disclose digital capability, regardless of changes in the underlying performance relationship.

2.3 Empirical Review

Numerous prior studies are most directly relevant to this study's constructs and context; however, they produced mixed results, possibly because of location, sector, population, and methodology.

- Bharadwaj (2000) studied a resource-based perspective on information technology capability and firm performance, using an archival financial-data study comparing IT-capability leader firms against a matched control sample over several years; he found that IT capability, defined as the ability to mobilise IT-based resources, is positively associated with superior firm performance.
- Melville, Kraemer and Gurbaxani (2004) examined Information technology and organisational performance: An integrative model of IT business value. Using a conceptual, integrative review of the IT business-value literature, he found that IT creates business value primarily through complementary organisational resources and competitive context, not technology spending alone.
- Mikalef and Pateli (2017) studied Information technology-enabled dynamic capabilities and their indirect effect on competitive performance:

Findings from PLS-SEM and fsQCA. Using survey data analysed with partial least squares structural equation modelling (PLS-SEM) and fuzzy-set qualitative comparative analysis (fsQCA), they found that IT-enabled dynamic capabilities affect competitive performance indirectly, through organisational agility.

- Wamba et al. (2017) Studied Big data analytics and firm performance: Effects of dynamic capabilities. Using survey-based structural equation modelling, he found that big data analytics capability is linked to firm performance through dynamic capabilities.
- Mikalef, Krogstie, Pappas and Pavlou (2020) Studied Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. Using survey-based structural equation modelling, they found that big data analytics capability's link to competitive performance runs through dynamic and operational capabilities.
- Li, Tong, Wei and Yang (2022) studied Digital technology-enabled dynamic capabilities and their impacts on firm performance: Evidence from the COVID-19 pandemic. Using panel data analysis of firm-level performance during the COVID-19 period, they found market-capitalising and operational-adjustment agility mediate the effect of digitalisation capability on firm performance.
- Homburg and Wielgos (2022) examined the value relevance of digital marketing capabilities to firm performance. Using archival analysis of secondary market and disclosure data and a value-relevance research design, they found that digital marketing capabilities carry demonstrable value relevance for firm performance.
- Chae, Koh and Prybutok (2014) examined Information technology capability and firm performance: Contradictory findings and their possible causes. Using a critical review and re-analysis of measurement practices across prior IT-capability studies, they found the IT capability-firm performance link is inconsistent across studies, and the inconsistency traces to measurement choices, context, and timing.
- Warner and Wäger (2019) studied Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal, using a qualitative, multiple-case study of established firms undergoing digital transformation; they found that digital sensing, seizing, and transforming routines form the microfoundations of strategic renewal in digital transformation.
- Sousa-Zomer, Neely and Martinez (2020) studied Digital transforming capability and performance: A microfoundational perspective. Using qualitative, case-based theory building, they found that digital transforming capability is a higher-order capability built from individual and organisational microfoundations.
- Guo, Li, Wang and Mardani (2023) studied: Does digital transformation improve the firm's performance? From the perspective of digitalization paradox and managerial myopia. Using a panel regression analysis of listed firms and a text-based digital transformation index, they found that digital transformation can raise productivity while lowering some measures of firm performance, a pattern they term the digitalisation paradox.
- Zareie, Attig, El Ghoul and Fooladi (2024) examined Firm digital transformation and corporate performance: The moderating effect of organisational capital. Using a panel data regression with a text-based digital transformation measure, they found that organisational capital and governance moderate the corporate value created by digital transformation.
- Karadağ, Şahin, Karamollaoğlu and Saunila (2024) studied Disentangling the dynamic digital capability, digital transformation, and organizational performance relationships in SMEs: A configurational analysis based on fsQCA. Using fuzzy-set qualitative comparative analysis (fsQCA) of survey data from SMEs, they found that combinations of dynamic digital capability and transformation conditions, not one universal path, predict higher SME performance.
- Dehnert (2020) studied sustaining the current or pursuing the new: Incumbent digital transformation strategies in the financial service industry. Using qualitative, comparative case analysis of incumbent financial-service firms, they found that digital-transformation strategies produce configurational, rather than uniform, performance effects.
- Karimi and Walter (2015) studied the role of dynamic capabilities in responding to digital disruption: A factor-based study of the newspaper

industry. Using a survey-based factor analysis of newspaper-industry executives, they found that US newspaper firms' ability to respond to digital disruption depended on dynamic capabilities built well before the disruption occurred.

- Liu, Chen and Chou (2011) examined Resource fit in digital transformation: Lessons learned from the CBC Bank global e-banking project. Using a qualitative single case study, they found that a resource-fit problem in the bank's global e-banking rollout limited the realised value of the digital initiative.
- Sebastian et al. (2017) studied how big old companies navigate digital transformation. Using a qualitative, multiple-case study of large incumbent firms, they found that large incumbents manage digital transformation by investing in operational backbones and customer-facing systems in parallel.
- Westerman, Bonnet and McAfee (2014) examined the nine elements of digital transformation. Using the conceptual framework derived from a multi-company survey and interview programme, they found that digital transformation requires organisational elements alongside technology, namely leadership, governance, culture, and workforce.
- Khin and Ho (2019) studied Digital technology, digital capability and organisational performance: A mediating role of digital innovation. Using a survey-based structural equation modelling with mediation analysis, they found that digital capability's effect on organisational performance runs through digital innovation, rather than acting directly.
- Grover and Kohli (2013) examined Revealing your hand: Caveats in implementing digital business strategy. Using a conceptual essay, they found that visible digital commitment does not prove realised value, since the same digital move can create value for one firm and destroy it for another.
- Samsuden, Kohar, Khatib and Abbas (2024) studied Digital capabilities and business performance: A systematic literature review. Using a systematic literature review synthesising 131 studies, they found that digital capabilities affect internal processes and performance, but results vary by context and performance measure.
- Abakpa and Dvouletý (2025) studied how digitalisation shapes business financial performance: A systematic review. Using a systematic literature review, they found that digitalisation can improve financial performance, though gaps remain around long-run outcomes and contextual conditions.
- Pavlou and El Sawy (2011) studied Understanding the elusive black box of dynamic capabilities. Using a survey-based empirical study of new product development teams, they found that variability in capability-performance findings traces to the unobserved "black box" of dynamic capabilities: sensing, learning, integrating and coordinating.
- Van de Wetering, Mikalef and Pateli (2021) studied A strategic alignment model for IT flexibility and dynamic capabilities: Toward an assessment tool. Using survey-based structural equation modelling, they found that IT flexibility and dynamic capability together, not either alone, determine whether digital resources turn into strategic outcomes.
- Fernandez-Vidal, Gonzalez, Gasco and Llopis (2022) studied Digitalization and corporate transformation: The case of European oil & gas firms. Using a qualitative, multiple-case study of European oil and gas firms, they found that digital transformation in this sector is a matter of governance, strategic alignment and organisational redesign, not simply technology acquisition.
- Maroufkhani, Desouza, Perrons and Iranmanesh (2022) examined Digital transformation in the resource and energy sectors: A systematic review. Using a systematic literature review, they found that digitalisation in resource and energy industries has concentrated on operational efficiency and cost reduction, with oil and gas underrepresented in the wider literature.
- Nwaiwu (2021) examined Digitalisation and sustainable energy transitions in Africa: Assessing the impact of policy and regulatory environments on the energy sector in Nigeria and South Africa. Using comparative qualitative policy analysis of Nigeria and South Africa, he found that policy and regulatory environments materially shape digitalisation and the energy transition in both countries.
- Chan, Sabherwal and Thatcher (2006) examined Antecedents and outcomes of strategic IS alignment: An empirical investigation. Using a survey-based structural equation modelling, they

found that IT resource's strategic value depends on the alignment between IT strategy and business strategy.

- Nevo and Wade (2010) studied the formation and value of IT-enabled resources: Antecedents and consequences of synergistic relationships. Using a survey-based quantitative study, they found that IT-enabled resource value arises from synergy between technology and complementary non-technical resources, not from either alone.
- Zhu, Kraemer and Dedrick (2004) studied Information technology payoff in e-business environments: An international perspective on value creation of e-business in the financial services industry. Using a cross-country survey-based empirical study of financial-services firms, they found that IT payoff in e-business environments depends as much on institutional and competitive context as on the technology itself.
- Brynjolfsson and Hitt (2000) studied Beyond computation: Information technology, organizational transformation and business performance. Using a review essay synthesising firm-level productivity studies, part of the foundational productivity-paradox literature, they found that Its business value is usually realised through complementary investment and organisational change, not through technology spending itself.

2.4 Gap in Literature

Measurement remains unsettled as much empirical work uses digital-word frequencies, broad adoption indicators, or survey scales that can flatten distinct digital capabilities into a single label. Evidence from African listed firms remain thin compared with China, Europe, and North America, and oil and gas research in particular remains a small share of the wider energy-digitalisation literature (Maroufkhani et al., 2022). Finally, many studies identify digital adoption without separating capability accumulation from value realisation, a distinction that matters because owning a system says little about how intensively it is used or how long benefits take to appear. No study identified here combines a multidimensional, contextually coded disclosure index with a longitudinal panel design and a regulatory-transition moderator in a Nigerian, or wider African, oil and gas setting. Closing that combined gap is the task of this study.

III. RESEARCH METHODOLOGY

3.1 Research Design

This study adopts a quantitative longitudinal panel design, with the firm-year as the unit of analysis. The design combines a qualitative, contextual content-analysis stage (used to construct the Digital Capability Disclosure Index from annual report text) with a quantitative panel-regression stage (used to test the association between that index and firm performance), described in full in the sections that follow.

3.2 Population of the Study

The study population comprises oil and gas companies listed on the Nigerian Exchange. Six firms (Seplat Energy Plc, Oando Plc, MRS Oil Nigeria Plc, TotalEnergies Marketing Nigeria Plc, Conoil Plc, and Eterna Plc) were continuously listed with complete audited financial statements throughout the 2016–2024 window and constitute the firms available for the study.

3.3 Sample Size and Sampling Technique

A purposive (census) sampling technique was used: all six oil and gas firms meeting the continuous-listing and complete-reporting criterion for 2016–2024 were included, rather than a random subset of a larger population. Firms that listed, delisted, or had gaps in their reporting history during the period were not eligible. That is why the resulting panel- six firms observed over nine years, for 54 firm-year observations- is small but balanced rather than large but patchy.

3.4 Data Collection Method

Two categories of data were collected from secondary sources. First, Financial and market data, namely total assets, total liabilities, shareholders' equity, profit after tax, share price, and shares outstanding, were extracted directly from audited annual reports, financial statements, and Nigerian Exchange (NGX) records for each of the six sample firms across the nine study years (2016–2024). Second, Digital-capability data were collected through structured, contextual reading of the same annual reports. Keyword searches (for example, "ERP", "SAP", "automation", "SCADA", "analytics", "artificial intelligence") were used only to locate candidate passages, and each candidate passage then had to describe a qualifying,

firm-specific capability, not a generic industry statement or aspirational language, before it was scored under one of the four DCDI dimensions. This process produced 216 construct-level coding decisions across the 54 firm-years and four dimensions, each supported by a recorded source passage and reasoning. The two data streams were then assembled into a single balanced firm-year panel dataset for the descriptive and regression analysis reported in Chapter Four.

3.5 Data Analysis Technique

Analysis proceeds in two broad stages. The first is descriptive: means, standard deviations, ranges and medians for all study variables, together with a regulatory-period comparison (Welch's t-test and a paired t-test) of DCDI and the three performance measures before and after 2020. The second is inferential: panel regression, estimated three ways for each performance outcome (pooled ordinary least squares, firm fixed effects, and two-way firm-and-year fixed effects), first for a baseline specification and then for a moderation specification that adds the regulatory-transition indicator and its interaction with DCDI. A supplementary dimension-level specification replaces the composite DCDI with its four component dimensions (EDS, DAIS, DMC, DADI), each estimated separately. All regressions use HC3 heteroskedasticity-consistent standard errors, and variance inflation factors are calculated to check for multicollinearity. Section 3.9 fully discusses the rationale for these choices and their limitations.

3.6 Model Specification

The study's models are specified as follows, where FP_it denotes firm performance (ROA, ROE, or Tobin's Q) for firm i in year t:

Baseline model: $FP_{it} = \beta0 + \beta1\ DCDI_{it} + \beta2\ SIZE_{it} + \beta3\ LEV_{it} + \varepsilon_{it}$

Moderation model: $FP_{it} = \beta0 + \beta1\ DCDI_{it} + \beta2\ RT_t + \beta3\ (DCDI \times RT)_it + \beta4\ SIZE_{it} + \beta5\ LEV_{it} + \varepsilon_{it}$

Dimension-level model: $FP_{it} = \beta0 + \beta1\ EDS_{it} + \beta2\ DAIS_{it} + \beta3\ DMC_{it} + \beta4\ DADI_{it} + \beta5\ SIZE_{it} + \beta6\ LEV_{it} + \varepsilon_{it}$

DCDI_it is the Digital Capability Disclosure Index; RT_t is the binary post-2020 regulatory-transition indicator; SIZE_it and LEV_it are the control variables; and ε_it is the error term. Firm fixed effects (α_i) and, in the two-way specification, year fixed effects (γ_t) are added to each equation in turn to absorb time-invariant firm differences and common year shocks, respectively. Chapter Four presents full estimation results for all three model families.

3.7 Data Collection Instrument

The study's primary data collection instrument for the independent variable is a purpose-built coding dictionary and evidence matrix, developed to convert qualitative annual-report disclosure into a structured measure of digital capability. The study defined and bounded four dimensions: Enterprise Digital Systems (EDS), Digital Automation and Intelligent Systems (DAIS), Digital Monitoring and Connectivity (DMC), and Data Analytics and Digital Innovation (DADI), each with an explicit coding rule specifying what counts and what is excluded. Each dimension is scored on a 0–2 scale: 0 (no qualifying disclosure after a reasonably thorough search), 1 (a substantive or planned capability), or 2 (a specific implementation, deployment, or operational use). An evidence matrix recorded the source passage and reasoning behind every one of the 216 construct-level coding decisions across the 54 firm-years and four dimensions, giving the index the same kind of content-validation trail that a qualitative item-generation exercise would produce for a survey instrument. For financial and market data, the instrument was more straightforward: a structured extraction template capturing total assets, total liabilities, shareholders' equity, profit after tax, share price, and shares outstanding directly from audited annual reports, financial statements, and Nigerian Exchange records.

3.8 Validity and Reliability of the Instrument

Construct validity rests on the explicit boundaries drawn between the four digital dimensions and the requirement that every score be supported by contextual evidence, recorded in the evidence matrix. A zero was only entered after a sufficiently broad negative search, limiting the risk of confusing non-disclosure with missing evidence. Beyond this content-validation trail, the constructed index was also checked quantitatively once assembled: variance inflation factor (VIF) diagnostics ruled out damaging multicollinearity between DCDI, the regulatory-transition indicator, and the control variables (reported in Chapter Four), and descriptive distributional checks

(mean, standard deviation, range, and dimension-level behaviour) confirmed the index behaves sensibly before use in the regression models. This quantitative check is not a substitute for a formal large-sample psychometric validation of the kind used for multi-item survey scales (for example, exploratory or confirmatory factor analysis across many raters); the DCDI is a document-coded disclosure index applied by the researcher to a fixed set of 54 firm-years, not a scale intended for repeated, independent human administration. Reliability, in the inter-rater sense, has not yet been established: an independent second coder has not yet applied the coding dictionary to the corpus, so no Cohen's kappa or weighted equivalent (Cohen, 1960) is reported here. This remains an outstanding requirement, not a completed step, and is addressed directly in Section 5.6.

3.9 Method of Data Analysis

Interpretation throughout gives more weight to effects that survive firm and year controls than to significance in the pooled model alone. HC3 heteroskedasticity-consistent standard errors are used rather than firm-clustered standard errors, because clustering assumes enough independent clusters for the sandwich estimator to behave well asymptotically, and six firms is too few for that to hold safely; HC3 is already conservative in small samples, which partly compensates, though this is treated as a specification choice worth flagging rather than a settled matter. No formal Hausman test was run to choose between random- and fixed-effects models because, with only six cross-sectional units, the test's usual asymptotics are unreliable; instead, pooled, firm fixed-effects, and two-way fixed-effects results are reported side by side. The two-way fixed-effects models are demanding for a panel this size, since firm and year dummies absorb a meaningful share of the available degrees of freedom. The R^2 values reported in Chapter Four should therefore be read as descriptive, not as evidence of a well-powered test.

3.10 Ethical Consideration

This study relies entirely on secondary, publicly available documentary data, namely audited annual reports, financial statements, and Nigerian Exchange records, and involves no human participants, surveys, or interviews, so no issue of informed consent, participant confidentiality, or personal data protection arises. All data sources and all cited literature are fully attributed. Coding decisions were documented with source passages and reasoning to ensure transparency and to avoid misrepresenting any firm's disclosure. No firm is named in a way that implies wrongdoing; the study reports patterns in disclosure and statistical association only, and does not make claims about any individual firm's motives or conduct.

3.11 A Priori Expectation

Based on the theoretical review (Section 2.2) and the research hypotheses (Section 1.5), the study holds the following a priori expectations about the sign and behaviour of each variable's coefficient in the performance equations.

Table 3.1: A priori expectations

Variable	Expected sign	Basis
DCDI	Positive	H01; resource-based view and dynamic capabilities theory
DCDI×RT (interaction)	Positive	H02; institutional theory (post-2020 regulatory transition)
DADI, relative to EDS/DAIS /DMC	Strongest positive signal	H03 (exploratory); higher-order capability framing
SIZE	Positive	Firm-performance literature scale and resource advantage

The DCDI and DCDI×RT expectations follow directly from the study's directional hypotheses rather than from settled prior evidence, and are treated as expectations to be tested against the data in Chapter Four, not as foregone conclusions. Where the empirical results in Chapter Four depart from these expectations, Sections 4.6 and 5.1 discuss that departure as a finding.

IV. DATA PRESENTATION, ANALYSIS, RESULTS AND DISCUSSION

4.1 Data Analysis Overview

This chapter presents the descriptive statistics, diagnostic checks, and regression results for the 54 firm-year observations (49 for ROE, after excluding five negative-equity firm-years). The chapter is

organised around two models: Model 1, the baseline association between DCDI and firm performance, and Model 2, the moderation model that tests whether the post-2020 regulatory transition changes that association. We first present and interpret descriptive statistics and baseline regression results (Sections 4.2–4.3), followed by the regulatory-period comparison, moderation regression results, and dimension-level robustness checks (Sections 4.4–4.5). Hypothesis decisions and an integrated discussion of results are presented in Section 4.6.

4.2 Presentation of Results

Table 4.1. Descriptive statistics (N = 54 firm-years, except ROE)

Variable	N	Mean	SD	Minimum	Median	Maximum
ROA	54	0.0230	0.0632	-0.2037	0.0291	0.1342
ROE	49	0.0843	0.3072	-1.2035	0.0868	0.7433
Tobin's Q	54	1.0232	0.3558	0.6393	0.9144	2.9940
EDS	54	0.6481	0.8502	0.0000	0.0000	2.0000
DAIS	54	0.7963	0.9786	0.0000	0.0000	2.0000
DMC	54	0.2222	0.5379	0.0000	0.0000	2.0000
DADI	54	0.0741	0.3281	0.0000	0.0000	2.0000
DCDI	54	0.2176	0.2241	0.0000	0.1875	1.0000
SIZE	54	12.2266	1.5775	10.2588	11.6210	16.1001
LEV	54	0.7141	0.1810	0.3590	0.7215	1.1575

Table 4.2. Model 1 — Baseline regression results (DCDI on firm performance)

Outcome	Specification	DCDI β	DCDI p	R^2
ROA	Pooled baseline	-0.0339	.508	.082
ROA	Firm FE baseline	-0.0286	.731	.349
ROA	Two-way FE baseline	-0.0424	.614	.490
ROE	Pooled baseline	-0.1440	.498	.021
ROE	Firm FE baseline	0.0101	.977	.415
ROE	Two-way FE baseline	-0.1911	.600	.622
Tobin's Q	Pooled baseline	-0.0847	.767	.123
Tobin's Q	Firm FE baseline	0.0104	.971	.331
Tobin's Q	Two-way FE baseline	-0.0223	.918	.648

Variance inflation factors are 1.099 for DCDI, 1.130 for RT, 1.120 for SIZE, and 1.117 for LEV — multicollinearity is not a material concern in the main composite specifications.

4.3 Interpretation of Results – Model 1

Mean DCDI is 0.2176, so disclosed digital capability is modest relative to the 0–1 scale's maximum. The component scores tell a more interesting story than the composite mean does: DAIS has the highest mean (0.7963 on its 0–2 scale), followed by EDS (0.6481), while DMC (0.2222) and DADI (0.0741) are far less common. The sample's digital profile is uneven. Enterprise systems and automation are visible far more often than connected operational technology and advanced analytics. ROA averages 2.30% (range -20.37% to 13.42%); ROE averages 8.43% but is more dispersed; mean Tobin's Q is 1.023, close to one for the average firm-year but with a long right tail.

DCDI is not statistically significant for any of the three performance measures in the baseline models, under any of the three estimators (pooled, firm fixed effects, two-way fixed effects). The coefficient sign is negative in most baseline specifications, contrary to the positive sign expected under H1 (Table 3.1), though none of these coefficients is distinguishable from zero. Read on its own, Model 1 gives no evidence that firms with higher disclosed digital capability report higher contemporaneous ROA, ROE, or Tobin's Q.

4.4 Interpretation of Results – Model 2

Table 4.3. Regulatory-period comparison

Variable	2016–2020 mean	2021–2024 mean	Welch p	Paired p
DCDI	0.1750	0.2708	.134	.125
ROA	0.0137	0.0347	.222	—
ROE	0.0549	0.1270	.437	—
Tobin's Q	0.9216	1.1501	.029	.063

Table 4.4. Model 2 — Moderation regression results (DCDI × regulatory transition)

Outcome	Specification	DCDI β	DCDI p	DCDI×RT β	Interaction p	R^2
ROA	Pooled moderation	-0.1443	.069	0.1557	.076	.224
ROA	Firm FE moderation	-0.1233	.321	0.1330	.160	.419
ROA	Two-way FE moderation	-0.1336	.283	0.1329	.160	.534
ROE	Pooled moderation	-0.6302	.256	0.6866	.250	.107
ROE	Firm FE moderation	-0.3359	.614	0.5048	.290	.446
ROE	Two-way FE moderation	-0.5952	.279	0.5437	.219	.653
Tobin's Q	Pooled moderation	-0.0821	.591	-0.1533	.797	.198
Tobin's Q	Firm FE moderation	0.1604	.584	-0.2539	.691	.358
Tobin's Q	Two-way FE moderation	0.2648	.351	-0.4181	.438	.661

Table 4.5. Dimension-level robustness (DADI on ROA)

Specification	DADI β	DADI p
Pooled	0.0379	.026
Firm FE	0.0337	.190
Two-way FE	—	.258

4.5 Interpretation of Results – Model 2

Mean DCDI rises from 0.175 in 2016–2020 to 0.2708 in 2021–2024, a difference of 0.0958 that is not statistically significant (Welch p = .134; paired p = .125). ROA and ROE also rise across the two periods but do not reach significance. Tobin's Q rises from 0.9216 to 1.1501, significant in the unadjusted Welch comparison (p = .029) but only marginal in the firm-level paired comparison (p = .063). This points to a later-period rise in disclosure and market valuation, not to evidence of a causal regulatory effect.

The pooled ROA moderation model initially suggests a change in the DCDI association after 2020 (DCDI p = .069; interaction p = .076), but this pattern fades once persistent firm differences are controlled for. The interaction's p-value rises to .160 under both firm and two-way fixed effects. The ROE and Tobin's Q interactions are not significant in any specification. In the dimension-level models, DADI is positively associated with ROA in the pooled specification (β = 0.0379, p = .026), but the association weakens sharply once firm fixed effects are added (p = .190) and further under two-way fixed effects (p = .258); EDS, DAIS and DMC show no robust significant effect on any performance measure.

4.6 Discussion of Results

Table 4.2 above presents Model 1's baseline regression results, Table 4.4 presents Model 2's moderation results, and Table 4.5 presents the dimension-level robustness results. Taken together, these results support the following hypothesis decisions:

- H01 is not supported. No statistically robust association appears between DCDI and ROA, ROE, or Tobin's Q in the preferred fixed-effects models of Model 1.
- H02 is not supported. In Model 2, the regulatory-transition interaction is not significant once firm differences and then common year effects are controlled for.
- H03 is weakly and only partially supported. The four dimensions differ, and only DADI shows a positive signal, consistent with the higher-order framing set out in Section 2.1.1.4, but the signal does not survive fixed effects.

Set against the a priori expectations in Table 3.1, the results depart from all three directional expectations: DCDI does not carry the expected positive sign in

most specifications, the DCDI×RT interaction does not hold up once firm and year differences are controlled for, and only DADI, and only in the pooled specification, shows the expected positive signal among the four dimensions. None of this shows that digital capability has no economic value; it shows that this study does not detect a stable, contemporaneous financial premium tied to higher disclosed digital capability. Chapter Five (Section 5.1) presents a fuller discussion of what this pattern means, set against the wider literature and the study's theoretical framework.

V. SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Discussion of Findings

Digital capability without an immediate performance premium. The central finding is a gap between growing disclosed digital capability and the absence of a robust, contemporaneous performance effect. This is not out of step with the wider literature: the strongest digital-capability studies increasingly describe value creation as mediated by agility, innovation, or process improvement, rather than as a direct technological return (Mikalef & Pateli, 2017; Li et al., 2022; Homburg & Wielgos, 2022; Zareie et al., 2024). One reasonable reading is that the sampled firms built up visible digital resources faster than they converted those resources into financial outcomes separable, statistically, from firm and year effects. Enterprise systems and automation dominate the disclosure profile, and these capabilities may improve control, compliance or process reliability without moving ROA, ROE or market valuation right away. Some of the benefits may also be defensive: avoiding downtime, protecting service quality, meeting regulatory requirements. That kind of benefit can matter economically without ever showing up as a discrete profitability gain. This also speaks to the older productivity-paradox tradition in information systems, which warned that IT's business value usually comes through complementary investment and organisational change, not spending on technology itself (Brynjolfsson & Hitt, 2000; Melville et al., 2004).

Why the regulatory interaction is weak. DCDI is higher in the later period, but the regulatory interaction is not robust to controls. One explanation is timing: regulatory transition can shift organisational priorities well before the economic returns to new capabilities become visible. Another is that the period indicator picks up a wide range of contemporaneous shocks (macroeconomic instability, exchange-rate movements, energy-market conditions, firm-specific restructuring) that cannot be pinned on regulation alone. A result (the pooled ROA interaction) that only appears before controlling for persistent firm differences is not strong evidence of anything in particular; the safer conclusion is that the data do not establish a stable moderation effect.

The uneven shape of digital capability. The component scores point to a second finding: digitalisation here is uneven. Enterprise systems and automation are far more visible than operational connectivity and advanced analytics, and different digital resources create value through different mechanisms. Treating all of this as one undifferentiated technology variable would hide that structure. The isolated pooled DADI result is worth a second look for this reason, even though it does not hold up under fixed effects: advanced analytics may sit closer to decision quality and resource allocation than basic infrastructure does, which could make its financial effect show up sooner once adoption is widespread enough (Gupta & George, 2016; Wamba et al., 2017; Mikalef et al., 2019).

Accounting versus market performance. The later-period rise in Tobin's Q is descriptively stronger than changes in ROA and ROE, but DCDI does not explain that rise in the panel models. Market valuation reflects expectations, strategic repositioning, commodity conditions, risk and investor sentiment, while accounting ratios reflect earnings already realised, measured against accounting bases. The pooled positive link between leverage and Tobin's Q also weakens under fixed effects, reinforcing a broader point about small-l panels: a strong pooled relationship can reflect persistent differences between firms rather than a real response to a changing explanatory variable.

5.2 Summary of Findings

Digital capability disclosure among the six sampled firms rose over the study period, driven mainly by enterprise systems and automation, with operational connectivity and analytics disclosed far less often.

That rise was not statistically significant on its own, and it was not accompanied by a statistically robust improvement in ROA, ROE, or Tobin's Q after controlling for firm and year differences. The post-2020 regulatory transition did not significantly change the DCDI–performance relationship in any preferred panel specification. A positive association between the data-analytics dimension (DADI) and ROA appeared in the simplest pooled model but did not survive adding firm fixed effects. On this evidence, all three hypotheses were either not supported (H1, H2) or only weakly and partially supported (H3).

5.3 Conclusion

This study examined digital capability disclosure and firm performance among six listed Nigerian oil and gas firms from 2016 to 2024, using a disclosure index built from enterprise systems, automation and intelligent systems, operational monitoring and connectivity, and data analytics and digital innovation. Disclosed digital capability became more prominent over time, but that rise did not translate into a robust, contemporaneous premium in ROA, ROE or Tobin's Q once firm and year differences were controlled for, and the post-2020 regulatory period did not produce a statistically reliable change in that relationship either. The better reading of this result is about conversion, not irrelevance: digital technology can improve information, coordination, monitoring and decision-making without producing an accounting or market effect that a small panel can isolate right away. The practical question these firms face is therefore not simply whether they are digitalising, but whether they pair digital resources with the routines, skills, governance, and organisational redesign needed to turn technological potential into measurable economic value. Digital capability is not a financial outcome in itself; its value depends on what the organisation does with it.

5.4 Contribution to Knowledge

This study contributes to knowledge in four ways. Conceptually, it draws a line between capability possession and capability realisation, treating digital capability as organisational potential that may or may not convert into measurable financial value inside a given window. As a measure, the DCDI is transparent and multidimensional: it separates enterprise systems, automation, operational connectivity, and analytics rather than collapsing them into a single digital word count, and its 0–2 scale distinguishes a substantive plan from an actual implementation. Empirically, it adds longitudinal evidence from a setting that is thin in a literature dominated by China, Europe and North America: Nigerian oil and gas. It combines asset intensity, institutional transition and emerging-market constraints in a way that tests whether widely reported digital-performance relationships hold outside the settings where they were first found. Theoretically, it connects the resource-based view, dynamic capabilities and institutional reasoning without forcing them into one deterministic model: digital resources create different kinds of potential across firms, dynamic capabilities govern how well that potential is reshaped and used, and institutions shape the incentives and constraints around the whole process. The absence of a clear, direct DCDI coefficient is itself informative, because it fits this account: it is consistent with organisational mechanisms sitting between owning a resource and realising its value.

5.5 Recommendations

The findings translate into concrete recommendations for four audiences: firm management, boards, regulators, and future researchers.

For firm management. Attach a written benefit map to every digital project before approval. Name the specific operational metric it is meant to move, such as downtime, cycle time, forecasting error, or safety incidents, and set a timeframe for checking whether it moved. Track realised benefits after go-live, not just deployment status, since this study finds that deployment alone does not show up as a performance premium.

Give the organisational side of digitalisation, such as training, process redesign, and data governance, at least as much weight as the technology purchase itself. The capabilities that showed the weakest link to performance here (enterprise systems, automation) are also the ones firms disclose most, while the one dimension with any positive signal (data analytics and digital innovation) is the one firms disclose least. Treat the current disclosure pattern as a prompt to invest more deliberately in analytics and data capability specifically, rather than adding more enterprise or automation systems on top of an already well-covered base.

For boards. Require a benefit-realisation review, not just a project-status update, at each major digital investment milestone. Ask management to report what changed operationally and what it was worth, not only what was installed. Where digital initiatives are disclosed to investors, push for disclosure language that says what the capability actually did, since vaguer disclosure is harder for outside readers, including researchers building measures like the DCDI, to verify.

For regulators and policymakers. Do not read rising digital disclosure after a regulatory transition as evidence that the transition is working, or that digital transformation is complete; this study finds the two are not reliably connected. Where disclosure requirements or incentives for digitalisation are being designed, build in a distinction between adoption (what was bought or built) and realised outcome (what changed as a result), since adoption is the easier thing to observe and the more likely thing to be rewarded by default. Support the data infrastructure that lets realised value follow adoption, such as reliable power, connectivity, and cybersecurity standards, since firms cannot convert capability into performance without it.

For future researchers. Extend this design to a larger panel of African energy or oil and gas firms before treating the null result here as settled, since the current sample is not well powered to detect a modest effect. Test one- and two-year lags to check whether the performance premium simply arrives later than this study's contemporaneous models can see. Complete an independent second-coder reliability exercise on the DCDI coding dictionary before relying on it elsewhere. Where possible, pair the disclosure-based measure used here with an instrumental-variable or lagged-predictor design that directly addresses reverse causality, and with mediator variables such as organisational agility, absorptive capacity, and managerial digital competence that could show how, not just whether, digital capability turns into performance.

5.6 Limitations of the Study

The first limitation is sample size (Although these are the listed firms with available records). Six firms observed over nine years provide a balanced longitudinal structure but little cross-sectional room to work with, so the models stay simple and the dimension-level estimates should be read cautiously. Second, DCDI measures disclosed capability, not the full stock or intensity of technology actually used inside the firm; annual reports vary in how they are written, and non-disclosure does not prove technological absence. Third, contemporaneous models can miss lagged returns, since digital systems often need implementation, learning and process redesign before financial benefits show up. Fourth, the regulatory-period indicator is deliberately broad and cannot isolate the causal effect of the Petroleum Industry Act from everything else that changed after 2020. Fifth, and separate from sample size, this design cannot rule out reverse causality: firms that are already performing well may simply have more resources to invest in digital systems and more reason to disclose them. That would produce the same null result reported here even if digital capability has no independent effect at all, or the opposite null result even if it does. Relatedly, because the sample is small, this study is not well positioned to detect a real but modest effect; the null result should be read as "not detected here" rather than "does not exist." Sixth, independent intercoder reliability still needs to be completed before this work is submitted for publication: the coding decisions reported here are documented and internally verified, but a defensible kappa statistic needs a second, independent coder applying the same coding dictionary to the full corpus or a defensible subsample, without seeing the first coder's scores in advance.

5.7 Suggestions for further Research

Future work should extend this design to more Nigerian listed firms, or build comparable panels across African energy markets, to gain the cross-sectional room this study lacks. It should triangulate annual-report coding against capital-expenditure data, technology job postings, patents, procurement records, interviews, or structured digital-maturity surveys, to check whether disclosed capability tracks actual technology use. Larger panels should test one- and two-year lags, distributed-lag structures, and non-linear effects, since Guo et al. (2023) suggest low, medium and high levels of digitalisation may have different performance consequences. More granular regulatory events, a difference-in-differences design with a credible comparison group, or firm-level

exposure measures would sharpen the regulatory-transition analysis considerably. An instrumental-variable design, or lagged predictors that at least weaken the simultaneity problem, would help address reverse causality directly. Finally, the capability–value realisation argument invites direct tests of mechanism: organisational agility, absorptive capacity, managerial digital competence, innovation capability, resilience, process integration and data-governance quality are all plausible mediators or moderators, and testing them would move the question from whether digitalisation pays off to how, when, and for whom it does.

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