

Data-Driven Decision-Making Adoption and Capability Development in Ghanaian Organizations: A TOE--RBV Perspective

Nana Assyne

Ghana Institute of Management and Public Administration <https://orcid.org/0000-0003-0469-6642>

Alfred Nyadroh

anyadroh@adj.gimpa.edu.gh

Ghana Institute of Management and Public Administration <https://orcid.org/0009-0004-6871-3127>

Joseph Budu

Ghana Institute of Management and Public Administration <https://orcid.org/0000-0002-0003-5807>

Emmanuel Antwi-Boasiko

Ghana Institute of Management and Public Administration <https://orcid.org/0000-0002-2301-0303>

Elizabeth Addy

Koforidua Technical University <https://orcid.org/0009-0007-2780-063X>

Felicia Engmann

Ghana Institute of Management and Public Administration <https://orcid.org/0000-0002-5812-1097>

Emmanuel Adabor

Ghana Institute of Management and Public Administration <https://orcid.org/0000-0003-4471-1915>

Isaac Wiafe

University of Ghana <https://orcid.org/0000-0003-1149-3309>

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Abstract

This study examines how Ghanaian organizations develop data-driven decision-making capability (DDMC), rather than merely adopting data tools. Anchored in the Technology-Organization-Environment (TOE) framework, the Resource-Based View (RBV), dynamic capabilities theory, and Simon's decision process logic, the study explains how data resources are transformed into decision intelligence, organizational routines, and maturity progression. Data were collected through 30 semi-structured interviews across healthcare, finance, technology, public administration, NGOs, manufacturing, real estate, and regulatory bodies. Thematic analysis identifies a four-stage maturity continuum and three interdependent data pillars: internally generated operational data, externally sourced strategic intelligence, and mandated compliance data. The findings show that data quality problems create a barrier chain that weakens later investments, while positive-deviant organizations build VRIN capability bundles around governance routines, leadership commitment, analytical culture, and decision review practices. The study positions DDMC as a dynamic capability that improves specific decision episodes such as resource allocation, revenue assurance, service redesign, compliance judgement, and risk response, and proposes maturity-aware strategies for Ghana and comparable developing economies.

1. Introduction

In an era of expanding data availability, the ability to convert raw information into actionable intelligence has become central to organizational competitiveness (Davenport & Harris, 2007; Provost & Fawcett, 2013). In this study, we define data-driven decision-making (DDDM) as the systematic use of relevant data, analysis, interpretation, and evidence to guide decisions rather than relying on intuition alone. Although DDDM is now an operational imperative, adoption remains uneven. High-income economies are moving toward predictive and prescriptive analytics, while resource-constrained settings still face infrastructure gaps, weak data quality, limited analytical skills, and fragmented governance (Avgerou, 2008; Heeks, 2002; Walsham, 1995).

Ghana provides a useful setting for examining DDDM in a lower-middle-income economy. The country combines expanding digital services and mobile penetration with persistent weaknesses in data literacy, governance, and interoperability (Ansong & Boateng, 2019). Ghanaian organizations now use data for hospital queue management, utility demand planning, media revenue verification, customer feedback analysis, and regulatory reporting. These examples reveal both the potential of DDDM and the uneven maturity of its adoption.

Despite increasing practitioner interest, DDDM adoption and capability development in Ghana and Sub-Saharan Africa remain thinly studied in three specific respects. First, existing African IS research has examined e-government (Heeks, 2002), mobile banking (Boateng et al., 2011), ERP implementation (Wamba et al., 2017), and big data analytics, but it has rarely explained how organizations convert data assets into repeatable decision routines and measurable decision quality. Second, available DDDM studies are often sector-specific, thereby limiting understanding of whether similar capability patterns

appear across healthcare, finance, government, NGOs, manufacturing, media, and technology organizations. Third, many studies emphasize technology adoption while giving less attention to the decision episode itself: what was being decided, which data informed the choice, who interpreted the evidence, and how the outcome fed back into organizational learning. This study therefore treats DDDM as decision-making capability development, meaning the organizational ability to define decision problems, mobilize credible data, analyse options, select evidence-based actions, and learn from outcomes.

To avoid treating DDDM as a broad and purely technical phenomenon, the study first conceptualizes it as a decision-making capability. The decision process is understood through Simon's intelligence-design-choice-review logic: organizations identify a decision problem, design evidence-informed alternatives, choose a course of action, and review outcomes for learning. This decision lens is then connected to a hybrid TOE-RBV-dynamic capabilities framework. TOE explains the technological, organizational, and environmental conditions that make DDDM adoption possible; RBV explains why some organizations convert similar data resources into superior capabilities; and dynamic capabilities theory explains how organizations sense data opportunities, seize them in decision routines, and reconfigure practices over time (Barney, 1991; DePietro et al., 1990; Teece et al., 1997).

The study is guided by one central research question: How do Ghanaian organizations develop data-driven decision-making capability from available technological resources, organizational routines, and environmental pressures? Three supporting questions focus the inquiry: (1) what data resources and analytics tools are used in specific decision episodes; (2) how do governance, leadership, skills, and culture enable or constrain the conversion of data into decisions; and (3) how do organizations progress across DDDM maturity levels under Ghanaian regulatory, infrastructural, and competitive conditions? This framing narrows the paper from a general study of "data" to an explanation of capability development, decision quality, and maturity progression.

The contribution is threefold. Empirically, the study provides a cross-sector baseline of DDDM capability development in Ghana. Theoretically, it integrates decision process logic with TOE, RBV, and dynamic capabilities, thereby explaining both how data enters decisions and why organizational outcomes differ. Practically, it identifies maturity-aware roadmaps for managers, policymakers, and development partners by linking intervention priorities to decision episodes, data quality foundations, governance routines, and analytical culture.

The paper proceeds as follows. Section 2 reviews literature on data analytics, decision making, and Ghana public organizations. Section 3 presents the theoretical framework. Section 4 explains the methodology. Sections 5 and 6 present findings and discussion. Sections 7 and 8 address limitations, future research, and conclusions.

2. Literature Review

2.1 Data Analytics

In this study, data analytics refers to the socio-technical process through which organizations collect, clean, integrate, analyze, interpret, and communicate data in order to produce decision-relevant evidence. This definition treats analytics as more than software use or statistical modelling. It includes data governance, data quality assurance, analytical skills, interpretation routines, and the organizational practices that convert analysis into action. Data-driven decision-making (DDDM), therefore, is defined as the use of relevant, credible, and interpreted data to inform managerial, operational, regulatory, and strategic decisions, while still allowing human judgment to evaluate context, ethics, and feasibility.

The dominant view in the analytics literature is that data becomes valuable when it improves decisions and organizational performance. Davenport and Harris (2007) describe analytics as a basis for competition, while Provost and Fawcett (2013) link data science to the systematic extraction of actionable knowledge from data. This view is echoed by Wamba et al. (2017), who argue that big data analytics contributes to firm performance when supported by dynamic capabilities. Within this logic, analytics capability does not reside only in the possession of tools such as Excel, SQL, Power BI, Python, or machine learning systems; rather, it lies in the organizational ability to repeatedly transform data into reliable insight.

Recent decision-support studies extend this position by shifting attention from prediction accuracy to decision usefulness. Wang et al. (2025) argue that analytics systems should be evaluated by the quality of decisions they enable, not merely by model performance indicators. Similarly, Elgendy et al. (2024) emphasise that data-driven decision evaluation requires organizational readiness, governance, integration, and analytical literacy. This perspective is important for the present study because many Ghanaian organizations may possess data and tools but lack the routines required to use analytical outputs consistently in decision processes.

The infrastructure perspective further shows that analytics capability depends on the reliability and interoperability of the data environment. Saunders et al. (2025) highlight uncertainty communication and reproducibility as conditions for reliable real-time decision support, while Carramiñana et al. (2024) show how risk-mitigation systems depend on data exchange and simulation capacity. Richetti et al. (2025) similarly demonstrate that AI-ready decision support requires harmonized data ecosystems rather than isolated datasets. These studies support the assumption that analytics maturity begins with foundational data quality and integration before advanced predictive or prescriptive analytics can generate value.

A second perspective focuses on trust, explainability, and interpretability. Khanizadeh et al. (2025) show that healthcare anomaly-detection systems are more useful when decision-makers can understand the pattern being flagged. Onari et al. (2024) also demonstrate that explainable decision-support systems become more actionable when users receive interpretable outputs and counterfactual guidance. This literature challenges the assumption that technically accurate analytics will automatically be accepted.

In practice, analytical outputs must be explainable, credible, timely, and aligned with the decision-maker's domain knowledge.

Alternative perspectives caution against treating analytics as a neutral technical solution. Socio-technical and interpretive information systems research argue that data systems are embedded in institutional rules, professional identities, organizational politics, and local meanings (Avgerou, 2008; Heeks, 2002; Walsham, 1995). From this perspective, weak DDDM outcomes may occur not because organizations lack data but because data are fragmented, contested, poorly governed, or inconsistent with how authority is exercised. Bostrom and Heinen (1977) socio-technical view further implies that technical investments must be aligned with work practices, incentives, skills, and structures.

The underlying assumption adopted in this study is therefore balanced. Data analytics is assumed to have strategic value, but only when it is embedded in organizational capabilities. Data are not treated as automatically objective, complete, or decision-ready. Instead, data become useful through governance routines, quality controls, analytical interpretation, and decision forums that allow evidence to influence action. This assumption directly supports the study's TOE-RBV framing, where technological resources become valuable only when combined with organizational and environmental capabilities.

2.2 Decision Making

Decision making is defined in this study as the organizational process of recognizing a problem or opportunity, selecting relevant evidence, comparing alternatives, authorizing a course of action, implementing that action, and learning from the outcome. This definition draws on Simon's (1977) view of managerial decision processes as structured around intelligence, design, choice, and review. For that reason, decision making is not treated as a single event but as a process shaped by information, judgment, authority, and feedback.

In DDDM research, decision making is often presented as a movement from intuition-led judgment to evidence-informed judgment. Korherr et al. (2022) show that digital transformation requires different managerial roles, including analytical thinkers, coaches, guides, and strategists, because analytics must be translated into managerial action. This suggests that DDDM is not simply a technical function delegated to analysts. It requires decision-makers who can ask appropriate questions, interpret outputs, challenge assumptions, and integrate data with organizational priorities.

Decision support literature also stresses that analytical systems must be tailored to the decision context. Di Caprio et al. (2025); Montlaur et al. (2023); Pignères et al. (2025); Sheikhhoshkar et al. (2025) show that decision support varies across sectors because each decision context has different objectives, constraints, risks, and accountability requirements. For example, flight-crew decision support prioritizes safety and time sensitivity, while public health workforce decisions require attention to retention, equity, and service continuity. This supports the assumption that DDDM capability must be assessed against the types of decisions an organization actually makes.

An important alternative perspective is that organizational decisions are not always rational, linear, or purely evidence-based. Decision-makers operate under bounded rationality, limited time, incomplete information, political pressures, and competing values. Knudsen et al. (2025) describe this as epistemic control: organizations must manage the tension between data-driven knowledge and experience-based knowledge. This is especially relevant to Ghanaian organizations where seniority, professional experience, and hierarchical authority may influence whether analytical evidence is accepted or ignored.

The literature also identifies the role of uncertainty. Shakibaei et al. (2025) and Singh, (2025) demonstrate that complex decisions often involve ambiguous data, competing criteria, and uncertain outcomes. Fischer-Abaigar et al. (2024) argue that public-sector algorithmic decision-making should explicitly define decision objectives, monitor feedback loops, and account for distributional effects. These studies challenge the assumption that dashboards or algorithms automatically improve decisions. They show that decision quality depends on whether uncertainty, bias, feedback, and human oversight are incorporated into the decision process.

A further assumption concerns the relationship between analytics and human judgment. This study does not assume that data should replace managerial judgment. Rather, it assumes that DDDM capability is strongest when evidence disciplines judgment without eliminating contextual reasoning. In lower-maturity organizations, experience may dominate data; in higher-maturity organizations, data and judgment are integrated through routines such as management dashboards, review meetings, decision checklists, audit trails, and performance evaluation systems.

For this study, decision quality is therefore defined as the extent to which decisions are evidence-informed, timely, transparent, contextually appropriate, and capable of being reviewed through feedback. This working definition is important because it shifts attention away from whether an organization owns advanced analytics tools and toward whether data meaningfully changes operational, strategic, regulatory, and service-delivery decisions. It also explains why the study examines maturity, governance, leadership, and analytical culture alongside tools and datasets.

2.3 Ghana Public Organisations

Ghana public organizations are defined in this study as state-owned, state-funded, state-regulated, or publicly mandated institutions that deliver public value, enforce rules, manage public resources, or provide essential services. They include ministries, departments, agencies, metropolitan, municipal and district assemblies, regulatory bodies, public hospitals, public utilities, and other organizations operating under public accountability expectations. Although the wider empirical sample includes private, non-governmental, and regulated organizations, the Ghana public-organization context is important because public rules, regulatory expectations, procurement systems, and service-delivery pressures shape the national data ecosystem within which DDDM develops.

The literature on information systems in developing economies provides the starting point for understanding DDDM in Ghana. Heeks (2002) argues that information systems initiatives in developing

countries often fail when there is a gap between system design assumptions and local realities. Avgerou (2008) similarly shows that IS adoption in developing economies must be understood through institutional, social, and political contexts rather than through technological availability alone. Walsham (1995) further supports interpretive analysis because organizational meanings and local practices shape how systems are used. These perspectives caution against importing analytics maturity models without adapting them to Ghanaian public-sector realities.

Ghana offers a distinctive public-sector setting for DDDM because digitalization ambitions coexist with infrastructural, skills, interoperability, and governance constraints. Ansong and Boateng (2019) show that digital enterprises in developing economies operate within resource limitations and evolving institutional environments. In public organizations, these limitations may be amplified by budget cycles, procurement delays, legacy systems, reporting hierarchies, and political oversight. Consequently, DDDM maturity in Ghana public organizations should not be interpreted only as a matter of technology adoption; it is also a matter of administrative capacity, accountability, and institutional coordination.

Public organizations also differ from private firms because their decisions must balance efficiency, legality, equity, transparency, and citizen trust. A private organization may use analytics primarily for revenue growth, customer targeting, or operational advantage. A public organization must also consider procedural fairness, public accountability, legal compliance, and potential effects on vulnerable groups. Fischer-Abaigar et al. (2024) warn that public-sector AI and analytics require decision objectives, feedback monitoring, human oversight, and attention to distributional consequences. This means that DDDM in Ghana public organizations should be evaluated not only by speed or efficiency but also by legitimacy and accountability.

Data governance is particularly important in Ghana because data use in public and regulated organizations must be compatible with legal and ethical obligations such as Data Protection Act (2012). In lower-maturity organizations, data protection may be perceived as a compliance burden that slows data sharing. In higher-maturity organizations, however, data governance can become a capability that strengthens trust, improves auditability, and creates confidence in data-based decisions. This assumption is consistent with the study's RBV logic: governance routines may become valuable, rare, inimitable, and non-substitutable when they are embedded in organizational practice rather than treated as external paperwork.

Alternative perspectives also show that analytics in public organizations can create risks. Widlak and Peeters (2025) argue that data-exchange infrastructures can affect procedural justice, organizational decision-making, and the meaning of data itself. Mahroof et al. (2025) similarly caution that AI-driven algorithmic decision-making in the public sector can reshape power dynamics. These perspectives are important because DDDM may improve service delivery while also increasing surveillance, reinforcing existing biases, or privileging technically measurable indicators over lived citizen experience. For Ghanaian public organizations, this implies that DDDM capability must be accompanied by transparency, accountability, and ethical review.

The reviewed literature reveals three assumptions that guide this study. First, data analytics is assumed to create value only when it improves real decisions rather than merely producing reports. Second, decision making is assumed to be socio-technical because evidence, human judgment, authority, culture, and incentives interact in the decision process. Third, Ghana public organizations are assumed to operate within a resource-constrained but institutionally important environment where data quality, governance, interoperability, skills, and political-administrative dynamics jointly shape DDDM maturity.

These assumptions reveal the gap addressed by this paper. Existing studies have examined analytics architectures, decision-support tools, data culture, algorithmic governance, and developing-economy IS adoption, but they often treat these issues separately. Less is known about how data analytics, decision making, and Ghanaian public-organization conditions interact to produce different levels of DDDM maturity. By organizing the literature around these three domains, this study positions DDDM as a capability that emerges from the alignment of analytical resources, decision routines, and Ghana-specific organizational conditions.

3. Theoretical Framework: A Hybrid TOE-RBV Model for DDDM

3.1 Decision Process Logic as the Decision Theory Anchor

The study anchors DDDM in Simon's decision process logic. This decision theory is appropriate because it specifies the stages through which evidence becomes action: intelligence, design, choice, and review. In the DDDM context, intelligence involves identifying the decision problem and locating relevant data; design involves analyzing options and consequences; choice involves selecting an action on the basis of evidence and managerial judgement; and review involves assessing whether the action produced the intended outcome. This decision lens narrows the study from broad data use to capability development around concrete decision episodes.

3.2 Technological Organisation Environment Framework

TOE explains the contextual drivers of DDDM adoption. The technology context includes data quality, interoperability, analytical tools, and infrastructure readiness. The organization context includes leadership support, skills, routines, culture, structure, and resources. The environment context includes regulation, competition, stakeholder pressure, data protection requirements, and national infrastructure. In this study, TOE does not predict adoption mechanically; instead, it identifies the pressures and conditions that shape whether organizations can begin or deepen DDDM practices.

3.3 Resource Based View

RBV explains why organizations exposed to similar technological and environmental pressures achieve different DDDM outcomes. The study operationalizes VRIN criteria in the DDDM context. A capability is valuable when it improves decision quality, reduces risk, or improves service and operational performance. It is rare when the organization possesses an uncommon combination of governance routines, analytical leadership, data-literate staff, and evidence-seeking culture. It is inimitable when

those routines are socially complex and path-dependent. It is non-substitutable when intuition or ad hoc reporting cannot produce comparable speed, reliability, or learning. Therefore, technology ownership alone is not classified as a VRIN capability; the strategic resource is the embedded capability bundle that converts data into decisions.

3.4 Dynamic Capabilities

Dynamic capabilities theory explains how DDDM capability develops over time. Sensing refers to the ability to identify data opportunities, decision pain points, emerging risks, and external intelligence. Seizing refers to the ability to embed analysis into dashboards, meetings, approval workflows, resource allocation, and strategic choices. Reconfiguring refers to the ability to redesign systems, retrain staff, revise governance rules, and retire practices that no longer support decision quality. These processes provide the mechanism linking TOE conditions and RBV resources to maturity progression.

3.5 Integrated Causal Logic of the TOE RBV DDDM Framework

The integrated framework proposes a clear causal explanation. First, TOE conditions create the opportunity and pressure for DDDM adoption. Second, organizations convert those conditions into outcomes only when they possess or build VRIN capability bundles. Third, dynamic capabilities mediate this conversion by enabling sensing, seizing, and reconfiguring. Fourth, the decision process lens specifies where capability is observed: in the quality of intelligence, design, choice, and review during specific decisions. Fifth, positive outcomes feed back into learning, which strengthens maturity; negative or unused outcomes reveal barriers such as poor data quality, weak leadership demand, or political interference. The framework therefore explains both how DDDM capability develops and why organizations facing similar pressures achieve different maturity levels.

Figure 1 presents the revised hybrid framework with explicit causal relations among contextual drivers, VRIN capabilities, dynamic capability processes, decision episodes, maturity, outcomes, and feedback learning.

3.6 Research Philosophy and Strategy

The study is positioned within an interpretivist research philosophy because it seeks to understand how organizational actors interpret data, negotiate evidence, and translate analytical outputs into decisions within their institutional contexts. Interpretivism is appropriate where the research objective is not to measure a single universal effect but to explain situated meanings, routines, tensions, and decision practices. The research strategy is an exploratory qualitative multi-sector study. It uses organizations as the context of inquiry and decision episodes as the unit of interpretation, enabling comparison of how DDDM capability appears across different Ghanaian sectors.

3.7 Research Design

This study employed an exploratory qualitative design to examine how Ghanaian organizations develop and operationalize DDDM capability. A qualitative approach is appropriate because the research question asks how and why decision routines emerge, become accepted, or fail to influence managerial action, issues that require contextually rich accounts rather than only numerical measurement (Creswell, 2014; Myers, 2020). The study is adductive: the TOE-RBV-dynamic capability framework provided sensitizing concepts, while the interview data refined the framework by revealing decision episodes, maturity tensions, and positive-deviant capability bundles (Alvesson & Sköldberg, 2009).

3.8 Sampling and Participants

Purposive sampling was used to recruit 30 professionals directly involved in strategic, operational, or technical aspects of data management and decision-making. The sample was constructed to maximize heterogeneity across sectors, organizational sizes, and professional roles, a strategy that enhances transferability by capturing the breadth of DDDM practices across Ghana's economy (Lincoln & Guba, 1985). Sectors represented include information technology, healthcare, finance and banking, real estate, manufacturing, non-governmental organizations, regulatory and government bodies, and education. Roles span senior leadership (CEOs, Managing Directors), data analytics professionals (data scientists, software engineers), operational and technical managers (IT managers, system administrators), and sector specific practitioners (pharmacists, monitoring officers).

Recruitment proceeded through a combination of professional networks affiliated with a leading Ghanaian management institution and targeted outreach to sector associations. Theoretical saturation, the point at which additional interviews generated no substantively new codes, was reached at approximately interview 26, and four additional interviews were conducted to confirm saturation (Guest et al., 2006). The predominantly urban composition of the sample (Accra and Kumasi) reflects the concentration of formal sector DDDM activity in Ghana but is acknowledged as a limitation that constrains transferability to rural and informal sector organizations.

3.9 Data Collection

Data were collected through semi-structured interviews conducted between January 2025 and June 2025. The interview guide was organized around the central research question and supporting probes on: (1) the specific decisions participants were involved in; (2) the data sources used for those decisions; (3) the tools and analytical routines used; (4) how evidence was interpreted, challenged, or accepted; (5) governance, privacy, and security practices; and (6) barriers, outcomes, and maturity progression. Each interview lasted between 45 and 75 minutes and was conducted face-to-face or virtually depending on participant availability. With informed consent, all interviews were audio-recorded and transcribed verbatim by trained research assistants. Transcripts were returned to participants for member checking, and clarifications were incorporated where participants corrected factual details or explained decision sequences more fully.

3.10 Justification for Interviews, Timing and Triangulation

Interviews were used as the primary data source because the study focuses on decision reasoning, organizational routines, and capability development, which are often not visible in organizational documents or system logs. The timing from January to June 2025 allowed participants to discuss recent reporting cycles, operational decisions, and technology investments within the same organizational year. Triangulation was applied at three levels: sector triangulation through participants from eight sectors; role triangulation through senior managers, analysts, IT staff, and operational practitioners; and theoretical triangulation through TOE, RBV, dynamic capabilities, and decision process logic. Documentary and system-level triangulation was limited because many organizations treated dashboards, reports, and internal data policies as confidential; this limitation is acknowledged, but the interview protocol reduced risk by asking for concrete decision examples rather than generic claims.

3.11 Data Analysis

Thematic analysis followed the six-phase process described by Braun and Clarke (2021): familiarization with data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. Coding combined inductive and deductive strategies. Deductive codes were derived from TOE, RBV, dynamic capabilities, and Simon's decision process stages. Inductive codes emerged directly from participants' accounts, including "Excel as decision infrastructure," "data quality barrier chain," "political override of technical recommendation," "single data champion fragility," "compliance as trust signal," and "meeting discipline as data culture." These inductive codes were later grouped into themes such as foundational data challenges, VRIN capability bundles, maturity tensions, and compliance-capability reframing.

Two researchers independently coded a randomly selected subset of 10 transcripts, then compared codes and reconciled disagreements through discussion, which is a dependability procedure that strengthens the consistency of the analytic process. Initial agreement across the 10 transcripts reached 81 per cent (calculated as agreements divided by agreements plus disagreements across all coded segments), and all residual disagreements were resolved through consensual discussion before any codes were applied to the remaining 20 transcripts (Lincoln & Guba, 1985). Thematic frequency charts were produced in Microsoft Excel to visualize the relative prevalence of codes; however, in keeping with the interpretive principles of thematic analysis, frequency was treated as a contextual indicator rather than a measure of significance (Braun & Clarke, 2021). Thick description of organizational contexts, supplemented by direct participant quotations, provides the primary basis for transferability claims.

3.12 Trustworthiness and Ethics

Trustworthiness was addressed across four criteria (Lincoln & Guba, 1985) and applied through concrete procedures rather than only textbook declaration. Credibility was supported by member checking of interview summaries, follow-up clarification on ambiguous decision examples, and the use of direct quotations to connect interpretations to participant accounts. Dependability was promoted through an audit trail that recorded coding decisions, changes to theme names, and reasons for merging or separating codes such as "skills gap" and "cultural resistance." Transferability was strengthened by

describing sector, role, organization type, and decision context so that readers can judge whether findings apply to comparable Ghanaian organizations. Confirmability was supported through reflexive memos in which the research team recorded assumptions about Western IS frameworks and tested whether Ghanaian evidence confirmed, modified, or challenged those assumptions.

Ethical approval was granted by the institutional Ethics Committee of the authors' affiliated institution, prior to data collection. Participation was voluntary and based on written informed consent. Organizational and individual identifiers were anonymized in all transcripts and outputs. All digital materials were stored on password protected, access controlled systems in line with institutional guidelines and Data Protection Act (2012).

4. Findings

This section presents thematic findings organized around the central research question and its supporting domains. The findings are not treated as six separate studies; rather, each theme explains one part of how Ghanaian organizations develop DDDM capability, how data enters specific decision episodes, and why maturity differs across organizations. Tables 1–6 summarize the coding structure, while the narrative interprets the decision logic behind the data practices.

4.1 What Technological Resources, Data Types and Tools, Do Organizations Deploy

Data Ecosystem: Three Interdependent Pillars

Organizations mobilize data across three thematic categories that together constitute their data ecosystem. The first, internally generated operational data, encompasses information produced through core organizational activities: transaction logs, patient records, commercial airtime data, HR metrics, and financial records. A banking sector participant described a fully integrated internal data environment: "Our data is primarily sourced from our central Oracle database, which aggregates information from all our banking applications, teller transactions, mobile banking, internet banking. Everything feeds into one place for analysis. We cannot make a lending or provisioning decision without first querying that system. (Banking sector participant, IT Manager)"

The second pillar, externally sourced strategic intelligence, captures data obtained from outside the organization for benchmarking and market positioning. Participants described sourcing data from industry associations, the Ghana Statistical Service, UNICEF reports, the Ghana Stock Exchange, and field collected primary data. An NGO participant explained: "We rely heavily on external data including poverty maps from the Ghana Statistical Service, district-level vulnerability indices from UNICEF, and our own field surveys. The external data tells us where the need is greatest; the internal data tells us whether our interventions are working (NGO sector participant, Monitoring and Evaluation Officer)"

The third pillar, mandated compliance and regulatory data, consists of information required for legal adherence and governance, non-negotiable and externally imposed. A legal sector participant underscored the consequential nature of this data category: "We cannot advise a client without first checking legal precedents in Westlaw and LexisNexis and cross-referencing the current regulatory position. That is not optional data work, it is the foundation of every case recommendation we make. (Legal services participant, Senior Associate)".

Table 1
Data Types and Sources in Ghanaian Organizations

Representative Keywords	Initial Codes	Theme	Conceptual Assertion
Customer data, workflow metrics, air-watch logs, financial records, patient data	Operational data; internal databases; digital system outputs	Internally Generated Operational Data	Organizations as continuous data producers: internal core
Ghana Statistical Service, UNICEF reports, Stock Exchange indices, field surveys, market research	Benchmarking; competitive intelligence; external research	Externally Sourced Strategic Intelligence	Environmental scanning through external lens: strategic positioning
Regulatory KPIs, legal precedents, compliance archives, Data Protection Act requirements	Mandatory reporting; governance obligations; legal data	Mandated Compliance and Regulatory Data	Non-negotiable data obligations: the regulatory rulebook

4.2 Tools and Technologies that are Used for Data Analysis

A four stage technology maturity spectrum emerged from the data, broadly consistent with the Gartner (2024), maturity models but situated within Ghana-specific enabling conditions. Unlike global frameworks, the Ghanaian spectrum reveals a significant mass of organizations anchored at Stage 1 and 2, with Stage 3 and 4 capabilities concentrated in larger, technology sector and healthcare organizations with external partnerships.

At Stage 1, ubiquitous and foundational tools, spreadsheets and manual processes dominate, sometimes out of necessity but also out of organizational habit: "We use Microsoft Excel extensively. Our senior analysts know Advanced Excel very well, pivot tables, VLOOKUP, conditional formatting, and for most of our reporting needs, it works. The question is whether it will continue to work as our data volumes grow. (Manufacturing sector participant, Operations Manager)."

Viewed through Simon’s decision process logic, fragmented data systems attack the intelligence stage specifically and foundationally. When data cannot be reliably aggregated, organizations cannot correctly define the decision problem the first and most critical stage of the Simon sequence. A compromised intelligence stage then propagates through the entire decision process: design alternatives are built on suspect inputs, choices are made under unnecessary uncertainty, and the review stage cannot distinguish genuine performance change from data artefact. This explains the hierarchical, cascading structure of the barrier chain: data quality is not simply one constraint among many, but the substrate on

which all subsequent Simon stages depend. Organizations that fail to secure the intelligence stage are structurally prevented from realising the value of investments made at the design, choice, or review stages – regardless of their analytical tool sophistication.

At Stage 2, established BI and data infrastructure, participants described the deployment of SQL databases, data warehouses, and visualization tools: "We use SQL for querying and managing large datasets and Power BI for visualization. Our IT department manages a data warehouse that consolidates data from different branches every night. This was a big investment three years ago, and it changed how our management team reads performance data. (Finance sector participant, Head of Analytics)."

Contrastingly, a participant from a smaller manufacturing firm at Stage 1 observed: "We are not fully digital yet. Some processes are still manual. We know it is a problem, but the cost of changing is significant." This contrast illustrates the infrastructure investment barrier that separates Stage 1 from Stage 2 organizations.

At Stage 3, specialized operational and functional systems, industry specific applications generate data as a by-product of operations: "We use an Electronic Health Records system and a Hospital Management System. The EHR alone generates thousands of data points daily, patient arrivals, diagnoses, treatment pathways, discharge times. The system was implemented with donor support, which helped with the cost. (Healthcare sector participant, Medical Director)"

At Stage 4, cutting-edge predictive and advanced analytics, a technology company and a healthcare organization illustrated the frontier: "We use Python for advanced data analytics, regression models, clustering, some machine learning. We also built a predictive model for patient readmission risk in partnership with a UK university. The model runs on historical discharge data and flags patients above a certain risk threshold for follow up calls. (Healthcare sector participant, Data Science Lead)."

Table 2
Tools and Technologies for Data Analysis

Representative Keywords	Initial Codes	Theme	Conceptual Assertion
Excel, manual processes, pivot tables, basic reporting	Spreadsheet analysis; experience-based methods; low-tech	Stage 1: Ubiquitous and Foundational Tools	Spreadsheet proficiency and experiential judgment as the entry level
SQL, Power BI, Oracle, Tableau, data warehouse	BI visualization; data centralization; self-service reporting	Stage 2: Established BI and Data Infrastructure	Data centralization and interactive reporting for mid-tier management
EHR, GIS, Kobo Toolbox, Westlaw, hospital management systems	Industry software; purpose built tools; operational data generation	Stage 3: Specialized Operational and Functional Systems	Operational data generation and sector specific analytics
Python, machine learning, predictive modelling, algorithm-based analysis	Advanced analytics; predictive modelling; in-house data science	Stage 4: Predictive and Advanced Analytics	Algorithmic decision-making and prescriptive intelligence

4.3 What Decisions Were Examined and How was Data Integrated into Operational and Strategic Decisions?

The analysis focused on identifiable decision episodes rather than data use in general. Across the interviews, the main decisions examined included whether to adjust advertiser invoices, how to allocate clinical staff during peak periods, where to site public infrastructure, how to redesign housing units based on occupant feedback, which districts should receive targeted NGO intervention, whether to flag high-risk patients for follow-up, and how to respond to system anomalies. This framing makes the decision object explicit and prevents the findings from being dominated by descriptions of data sources alone.

Five logics of data use emerged from participants' accounts of how data is mobilized in decision-making. These logics form a progression from reactive operational control toward proactive strategic foresight, broadly mirroring the descriptive to prescriptive analytics trajectory described by Provost and Fawcett (2013), but revealing Ghana specific applications at each stage.

Mapped onto Simon's intelligence–design–choice–review logic, each of the five logics corresponds to distinct stages of the decision process. Tactical improvement is anchored in the intelligence stage (recognising a process problem and locating operational data). Strategic governance engages the design stage (assembling evidence-based alternatives for infrastructure or policy decisions). Market and customer responsiveness operates at the choice stage (selecting service adaptations informed by demand signals). Human capital development reflects a design–choice sequence applied to programme evaluation. Proactive adaptation represents the most complete Simon cycle: sensing anomalies in real-

time data (intelligence), assembling response options (design), triggering intervention (choice), and confirming resolution before harm materialises (review). This mapping makes Simon's stages analytically operational across the findings, rather than treating them as a background framing concept.

The first logic, tactical and operational improvement, was the most widely described and involves using data to optimize day to day processes: In the media case, the specific decision was whether to approve, adjust, or dispute advertiser invoices after comparing contractual airtime obligations with verified broadcast logs. The data therefore served as evidence for a revenue assurance decision, not simply as a record of commercials played. "Data from our air watch system shows exactly which commercials played, at what time, and for how long. We compare that against what the advertiser paid for, and if there is a discrepancy, we have evidence to correct the invoice. That one data application alone secured a significant amount of previously unrecovered revenue. (Media sector participant, Chief Revenue Officer)."

In healthcare, the same logic manifested in resource allocation: "By analysing patient arrival data and staffing patterns, we identified that our peak emergency arrivals are between 9 a.m. and 1 p.m. We adjusted our triage staffing accordingly and reduced average wait times by approximately 20 per cent." (Healthcare participant, Operations Manager). This episode illustrates a complete Simon cycle. Intelligence: arrival data reveals that peak emergency volume occurs between 9 a.m. and 1 p.m., defining the decision problem as a staffing mismatch rather than a general capacity shortage. Design: roster alternatives are modelled against arrival patterns. Choice: triage staffing is reallocated to the peak window. Review: the 20 per cent reduction in average wait time provides feedback that validates the choice and anchors future staffing decisions. The cycle's completion including the review stage – distinguishes this organization from lower-maturity peers where decisions are made but outcomes are rarely measured back against the original data.

The second logic, strategic and regulatory governance, applies data to long range planning and compliance: "Data on flood frequency, waste disposal patterns, and drainage catchment areas was central to the decision about where to site the new retention basins. Without that spatial data layer, we would have been guessing. Approximately 80 per cent of our significant infrastructure decisions are backed by scientific data analysis. (Public sector participant, Infrastructure Planning Officer)".

The third logic, market and customer responsiveness, uses data to adapt offerings to demand signals. A real estate company's experience was particularly vivid: "We asked occupants systematically what was working and what was not. One hundred per cent reported that the absence of an additional washroom in two-bedroom units was a major issue. The data made a clear recommendation. The next development phase included the additional washroom, and occupancy rates in those units have been higher. (Real estate participant, Development Director)"

The fourth logic, program and human capital development, focuses on using data for evaluation and staff development. An NGO participant described:

"Survey data revealed a 43 per cent dropout rate among girls in three northern districts, with sanitation as the primary reason cited by parents. That single finding redirected our partnership strategy, we went from general education programming to targeted school sanitation investment in those districts. (NGO participant, Programme Manager)". In Simon's terms, the field survey constitutes the intelligence stage: the 43 per cent dropout finding redefines the decision problem from "how to improve general education attendance" to "how to address sanitation-driven non-enrolment in three specific districts." The design stage involves comparing programming alternatives (broad education investment versus targeted sanitation infrastructure). The choice stage is the strategic reallocation of partnership resources toward school sanitation. Notably, the account does not describe a subsequent review stage – no follow-up measurement of dropout rates post-intervention is reported. This gap is theoretically significant: it suggests that even relatively capable NGO organizations may execute intelligence and choice reliably while under-institutionalizing the review stage that would close the learning loop.

The fifth logic, proactive adaptation and validation, represents the most advanced decision use because data is used to decide whether to intervene before a problem becomes visible to most stakeholders. The decision object is not the data pattern itself but the managerial action triggered by the pattern, such as assembling a crisis team, contacting high-risk patients, adjusting system capacity, or validating whether a pilot intervention should be scaled. "Our login framework flagged an unusually high failure rate on a particular mobile device model, a pattern that would not have been visible without real-time analytics. We assembled a crisis team within 20 minutes. The issue was resolved before most users even encountered it. (Technology sector participant, CTO)".

This episode represents Simon's decision process at its highest maturity. The analytics system performs the intelligence function autonomously and near-instantaneously, flagging an unusual device-specific failure rate that human monitoring would have missed. The design stage is compressed by the crisis team structure pre-defined response protocols reduce deliberation time. The choice stage (assembling the team and initiating remediation) is executed within 20 minutes. Critically, the review stage operates in real-time: issue resolution is confirmed before most users encounter the problem, meaning the feedback loop closes within the same operational cycle rather than in a retrospective reporting period. This is the only episode in the data where all four Simon stages are observable within a single, time-bounded decision event a characteristic of Stage 4 DDDM maturity.

Table 3
Data Integration into Operational and Strategic Decisions

Representative Keywords	Initial Codes	Theme	Conceptual Assertion
Revenue assurance, staffing optimization, queue management, cost reduction	Operational efficiency; financial control; process improvement	Tactical and Operational Improvement	Data as an efficiency engine: process and revenue optimization
Infrastructure siting, regulatory compliance, risk management, evidence based policy	Long range planning; regulatory adherence; risk aversion	Strategic and Regulatory Governance	Data as a governance instrument: evidence based strategy
Customer feedback loops, demand signals, segmentation, market intelligence	Customer intelligence; market alignment; service personalization	Market and Customer Responsiveness	Data as a market sensor: customer centric adaptation
Dropout rates, skill gaps, impact evaluation, staff development	Program evaluation; workforce optimization; impact assessment	Program and Human Capital Development	Data as an organizational learning mechanism
Real-time anomaly detection, crisis response, pilot validation, proactive risk sensing	Predictive intervention; systemic monitoring; validation	Proactive Adaptation and Validation	Data as a strategic radar: anticipatory intelligence

4.4 What Environmental Conditions Constrain or Enable DDDM Adoption?

Four thematic clusters of challenges emerged, forming a hierarchical chain of constraints in which lower tier failures cascade into upper tier barriers.

The foundational tier, data quality and fragmentation, was the most frequently cited challenge and constitutes the substrate on which all other DDDM capability depends: "The fundamental problem is that our data quality is inconsistent. Regional offices submit returns in different formats, with different definitions of the same variable. When I try to aggregate at the national level, I am comparing apples with oranges. Any analysis built on that foundation is suspect. (Regulatory body participant, Data Analytics Specialist)."

"We have five different software applications that do not talk to each other. Finance uses one system, operations uses another, HR uses a third. To get a complete picture, someone has to manually export from each system and assemble a spreadsheet. That takes two days and introduces errors at every step. (Manufacturing sector participant, Operations Manager)"

The human capital tier encompasses skills gaps and cultural resistance, the organizational engine that drives DDDM even when data quality is adequate: "We have data analysts, but we do not have a data

scientist who can build predictive models from scratch. So we are limited to descriptive and some diagnostic analytics. We can tell you what happened, and sometimes why, but we cannot yet tell you what will happen. (Finance sector participant, Head of Analytics)"

"The cultural challenge is significant. Some senior managers have built their careers on experience and judgment. Asking them to defer to a model feels like a challenge to their professional identity. The conversation I have is not "the data says you are wrong", it is "the data gives you more information to make the decision you would make anyway." That framing helps. (Technology sector participant, Head of Data)"

The technological and financial tier captures infrastructure and budget constraints: "The licensed software we need costs more than our entire technology budget for the quarter. Some of my colleagues use cracked versions, pirated software. That creates security risks and reliability problems. It is a pragmatic response to an impossible budget constraint, but it is not a sustainable solution. (Media sector participant, IT Manager)".

The structural and environmental tier includes political interference and external volatility, particularly significant in the public sector: "There are decisions where the technical recommendation is clear, but the appointed board prioritizes political considerations. I present the data. The decision goes a different way. This is not corruption, it is politics. But it means the analytical work has no impact. (Public-sector participant, Chief Planning Officer)."

Table 4
Environmental Conditions Constraining DDDM Adoption

Representative Keywords	Initial Codes	Theme	Conceptual Assertion
Poor data quality, inaccurate records, inconsistent formats, data silos	Data quality issues; fragmentation; integration failures	Foundational Data Challenges	Tier 1: Unreliable data and fragmented access undermine all analysis
Skills shortage, data literacy gaps, cultural resistance, resistance to evidence	Talent gap; change aversion; intuition preference	Human Capital and Cultural Resistance	Tier 2: Lack of analysts and aversion to change limit organizational capacity
Outdated systems, pirated software, budget constraints, infrastructure deficits	Legacy systems; cost prohibition; connectivity gaps	Technological and Financial Barriers	Tier 3: Legacy infrastructure and underfunding starve DDDM initiatives
Political interference, bureaucratic inertia, unpredictable external conditions	Governance issues; regulatory ambiguity; external volatility	Structural and External Headwinds	Tier 4: Bureaucratic inertia and political dynamics override technical recommendations

4.5 Where Do Organizations Sit on the DDDM Maturity Continuum, and What Differentiates Higher Maturity Adopters?

A distinctive contribution of this study is the identification of positive deviant organizations, those that achieve higher than expected DDDM maturity given their environmental constraints. Analysis of these cases reveals that superior maturity is not primarily a function of organizational size or sector, but of specific VRIN capability bundles. Three factors consistently distinguished higher maturity organizations from their peers: leadership commitment to evidence-based decision-making, deliberate investment in data governance routines, and the cultivation of an analytical culture through structured training and performance incentives.

The healthcare Stage 4 organization provides the clearest positive deviant case. Operating in a resource constrained public health environment, it achieved predictive analytics capability through a combination of a data championing Medical Director, a partnership with an international university, and a governance structure that embedded data review into weekly clinical management meetings: "The Medical Director is obsessed with data. Every management meeting starts with a 20-minute data review, we look at admission trends, readmission rates, near miss incidents. That discipline cascades down. People know that if they cannot show the data, their operational recommendation will not be heard. (Healthcare participant, Quality Assurance Manager)"

By contrast, a demographically similar organization in the same sector, same size, same sector, similar infrastructure remained at Stage 1 because its senior leadership had not institutionalized data review processes: "Management meetings are mostly verbal updates. The CEO is very experienced and tends to go with his judgment. We have data, but it is not part of the decision rhythm. People present reports, but they are not used to question or validate decisions. (Healthcare participant, IT Systems Analyst)". This contrastive analysis strongly supports the VRIN logic: leadership commitment (Valuable), analytical culture (Rare and Inimitable), and governance routines (Non-substitutable), not technology alone, explain differential maturity outcomes.

The same contrast is analytically visible through Simon's decision process lens. The Stage 4 healthcare organization executes all four stages systematically: intelligence is institutionalized through weekly data reviews that surface operational problems before they escalate; design is supported by predictive readmission models that generate evidence-based intervention options; choice is anchored in evidence-bound clinical governance; and review is embedded in outcome-monitoring cycles that feed back into model refinement. The Stage 1 peer organization, by contrast, remains functionally locked at a fragmented intelligence stage. Reports are produced and presented, but there is no organizational routine that converts data into a structured problem definition leaving design, choice, and review stages poorly served regardless of available technology. This Simon-stage contrast provides a more granular

explanation of differential maturity than VRIN criteria alone: it reveals not just that the organizations differ in capability but precisely where in the decision process that capability deficit is located.

Table 5
DDDM Maturity Continuum and VRIN Capability Differentiation

DDDM Stage	Dominant Tools	VRIN Capability Level	Differentiating Factor
Stage 1: Manual and Spreadsheet	Excel, manual processes	Low, tools widely available, no governance routines	No data review culture; intuition dominant decisions
Stage 2: Business Intelligence	SQL, Power BI, data warehouse	Moderate, BI infrastructure rare in sector	Structured reporting; partial management buy in
Stage 3: Specialized Systems	EHR, GIS, industry platforms	Moderate-High, sector-specific, partially inimitable	Domain expertise embedded in purpose-built tools
Stage 4: Predictive Analytics	Python, ML models, real-time monitoring	High, VRIN bundle: leadership + culture + governance	Leadership champion + governance routines + external partnerships

4.6 What Future Opportunities Can Strengthen DDDM Capability in Ghana?

Four thematic opportunity clusters emerged from participant accounts of desirable futures and observed capability gaps.

Predictive analytics and IoT integration represented the most frequently anticipated technological opportunity, with participants describing a desire to move from understanding the past to anticipating the future: "We want to move from "what happened last month" to "what will happen next month." That means building time-series models on our operational data and integrating real-time feeds from IoT sensors on our infrastructure. We are not there yet, but it is where we are heading and it is what our regulatory environment will soon require. (Utility sector participant, Head of Operations)"

Unified and interoperable data architectures were identified as the enabling condition for advanced analytics: "The opportunity that excites me most is breaking down the data silos. If our ERP, our CRM, and our logistics system were feeding into a single data lake, we could ask questions that are currently impossible. Right now, we cannot even answer "which customers are most profitable to serve" without a three-day manual exercise. (Real estate participant, Chief Operating Officer)"

Workforce development and data culture were consistently identified as the highest leverage investment: "Technology is the easy part, you buy it, you configure it. The hard part is building a workforce that knows how to use it and a culture that demands evidence. That takes years, and it starts with leadership. If the CEO does not ask for data, nobody will bother producing it. (Finance sector participant, Chief Information Officer)."

Data governance and trust building were recognized as foundational enablers, particularly given Ghana's Data Protection Act (2012): "We see data protection compliance not as a burden but as a competitive differentiator. We can say to clients: your data is governed, secure, and handled by people who have been trained in data ethics. That builds trust, and trust builds business. (Technology sector participant, Data Privacy Officer)."

Table 6
Future Opportunities for DDDM in Ghana

Representative Keywords	Initial Codes	Theme	Conceptual Assertion
Predictive models, IoT sensors, AI automation, real-time monitoring	Advanced analytics; predictive power; automation	Leveraging Cutting Edge Technology for Foresight	Predictive intelligence and real-time response as the technological frontier
Data lake, ERP integration, unified architecture, centralized data entry	System integration; data centralization; interoperability	Creating Unified and Interoperable Data Architectures	360-degree organizational intelligence through seamless integration
Staff training, data literacy, leadership buy-in, analytical culture	Capacity building; cultural transformation; evidence based mind-set	Building a Data-Driven Workforce and Culture	The human pillar: skills, culture, and leadership as the highest leverage investments
Data Protection Act compliance, cybersecurity, governance frameworks, transparency	Ethical data use; regulatory leadership; security	Establishing Trust as a Foundational Enabler	Trust as competitive differentiator: governance enables broader data ambition

Cross-cutting Analytic Synthesis and Theoretical Interpretation. Viewed across all themes, the findings explain how and why DDDM capability develops unevenly in Ghanaian organizations. The first explanation is a capability-sequencing effect: organizations cannot move from descriptive reporting to predictive or prescriptive decision-making when data quality, interoperability, and governance remain weak. This explains why many participants aspire to advanced analytics but remain anchored at Stage 1 or 2. In TOE terms, the technology context constrains the feasible decision space; in RBV terms, basic tools are not strategic resources until embedded in routines; and in dynamic capability terms, weak sensing prevents effective seizing and reconfiguring.

The second explanation is an institutionalization effect. Positive-deviant organizations did not outperform peers merely because they had better software; they had repeated decision rituals such as management meetings that began with data reviews, leadership questions that demanded evidence, and routines that linked analytical outputs to action. These practices converted data into a VRIN capability bundle because they were valuable, uncommon, socially complex, and difficult to substitute with

intuition. However, the same finding also reveals fragility: when DDDM depends on a single champion, capability remains vulnerable unless it is procedural across roles and management layers.

The third explanation is a compliance-capability reframing effect. Lower-maturity organizations experienced data protection and reporting requirements mainly as cost and constraint. Higher-maturity organizations reframed the same requirements as governance infrastructure that builds trust and legitimacy. This is a theoretically important finding because it shows that the same environmental pressure can have opposite effects depending on organizational capability. Therefore, the paper's contribution is not only descriptive; it explains that DDDM maturity in Ghana emerges when organizations sequence data foundations, institutionalize decision routines, and convert compliance into trust-building capability.

5. Discussion

5.1 DDDM Maturity in Context: Extending and Localizing Existing Frameworks

The four-stage maturity spectrum identified in this study is broadly consistent with established analytics maturity models (Davenport & Harris, 2007), confirming that the descriptive to predictive trajectory documented in high income economies is recognizable in the Ghanaian context. However, the study extends these frameworks in three important ways. First, it shows that the distribution of organizations across the maturity continuum is heavily skewed toward Stages 1 and 2 in Ghana, a skew that is not captured in Western maturity models calibrated against capital intensive manufacturing and financial services sectors. Second, it identifies the specific environmental contingencies, infrastructure deficits, budget constraints, and political interference, that suppress maturity progression in ways that Western models do not theorize. Third, and most importantly, it demonstrates that maturity is not a deterministic function of organizational size or sector, but of VRIN capability bundles, a finding with significant practical implications for how organizations and policymakers should prioritize investments. Taken together, these three extensions suggest that global maturity models require a developing-economy variant that weights environmental contingencies and capability composition more explicitly than existing frameworks do. Future IS adoption researchers applying maturity frameworks in Sub-Saharan Africa, South Asia, or other resource-constrained settings should treat the Stage 1/2 concentration not as a temporary lag but as a structurally distinct adoption regime requiring its own theoretical treatment.

A fourth extension to existing maturity models concerns the relationship between maturity stage and Simon's decision process stages. This study's evidence suggests that maturity progression can be understood as the sequential institutionalization of Simon's four stages: Stage 1 organizations execute only fragmented intelligence, often informally; Stage 2 organizations regularize intelligence and introduce structured design through BI dashboards and reporting cycles; Stage 3 organizations embed domain-specific tools that support reliable, repeatable choice within defined operational domains; and Stage 4 organizations close the review loop through predictive feedback mechanisms and systematic

organizational learning. This mapping provides a theoretically grounded explanation for why maturity advancement is non-trivial: each stage transition requires not merely new technology but the organizational routines, governance structures, and leadership behaviours that operationalize the next Simon stage. It also explains why technology investment alone rarely advances maturity tools purchased for the design or choice stage deliver limited value when the intelligence stage remains unreliable.

5.2 Operationalizing VRIN in the DDDM Context

A central theoretical contribution of this study is the operationalization of Barney (1991) VRIN criteria in the DDDM domain, extending Wade and Hulland's (2004) IS application of RBV to a developing economy analytics context. The analysis yields four specific VRIN findings. Value is realized when analytical outputs are embedded in organizational decision rhythms, in management meeting agendas, operational dashboards, and governance committee presentations. Organizations where data review is a routine, rather than an exceptional, activity consistently reported higher decision quality and faster response times. Rarity inheres in coherent combinations of governance routines, leadership commitment, and analytical culture: while each element is conceptually familiar, their coherent integration in the Ghanaian context, where each faces independent headwinds, is uncommon. Inimitability arises from the path dependent nature of analytical culture: the healthcare organization that achieved Stage 4 maturity did so through years of accumulated investment in data infrastructure, staff capability, and management routines that cannot be replicated overnight through technology purchase. Non-substitutability is demonstrated by the limitations of intuition dominant alternatives: participants who described purely experience-based decision-making consistently reported slower identification of operational problems, less accurate revenue forecasting, and greater exposure to compliance risk. To reduce the risk of treating these as merely complementary resources rather than a genuine VRIN bundle, the analysis applied each VRIN criterion as a disconfirmation test: resources that satisfied fewer than three of the four criteria were classified as competitive parity factors rather than VRIN elements. Under this coding rule, technology infrastructure (widely procurable) and basic data literacy training (transferable) were excluded from the VRIN bundle, while the combination of embedded governance routines, leadership advocacy, and institutionalized analytical culture met all four criteria. This criterion-by-criterion coding procedure, while not constituting a pre-registered measurement instrument, provides a more systematic basis for the VRIN assertion than descriptive label alone.

5.3 Dynamic Capabilities and the Sensing Seizing Reconfiguring Logic

Dynamic capabilities theory (Teece et al., 1997) provides the mechanism that RBV alone cannot supply: an explanation of how organizations move between maturity stages. The data support a three phase capability building logic. Sensing the capacity to identify relevant data sources and analytical possibilities is demonstrated by organizations that systematically audit their data assets, scan industry associations for benchmarking data, and participate in regulatory working groups that signal upcoming data requirements. Seizing, embedding analytics into decision workflows is demonstrated by organizations that redesign their management meeting structures around data review, invest in BI

visualization tools that make analytics accessible to non-technical managers, and incentivize data informed recommendations in performance evaluations. Reconfiguring updating architectures and skill bases in response to environmental change is demonstrated by organizations that retired legacy systems, established data governance committees, and partnered with international research institutions to access analytical capabilities they could not build internally. The positive deviant healthcare organization exemplifies all three capabilities; the Stage 1 peer organization exemplifies none.

Simon's decision process logic specifies where each dynamic capability is observable within the decision sequence. Sensing operates primarily at the intelligence stage: organizations with strong environmental scanning capabilities identify data opportunities and decision problems earlier and more accurately. Seizing operates at the design and choice stages: embedding analytics into workflows enables the construction of evidence-informed alternatives and the selection of defensible actions that can be audited and justified. Reconfiguring operates most directly at the review stage: organizations that systematically redesign governance routines and retrain staff in response to decision outcomes are, by definition, closing the feedback loop that Simon's model identifies as the mechanism of organizational learning. The convergence of Teece et al.'s (1997) sensing–seizing–reconfiguring logic with Simon's intelligence–design–choice–review sequence thus provides a more complete theoretical account of DDDM capability development: dynamic capabilities explain the organizational processes, while Simon's stages specify the decision-process locations at which those processes must be active to produce capability improvement.

5.4 Environmental Contingencies: The Ghanaian Context as Both Constraint and Catalyst

The TOE environmental dimension reveals that Ghana's regulatory and infrastructural conditions simultaneously constrain and catalyze DDDM adoption. Ghana's Data Protection Act (2012), for example, is experienced by smaller organizations primarily as a compliance burden, a source of uncertainty and cost. However, larger and more mature organizations, particularly in technology and financial services, have internalized data protection compliance as a VRIN resource: their demonstrated capacity to handle client data responsibly becomes a trust-based competitive differentiator that smaller, less governed competitors cannot easily replicate. This finding aligns with Fischer-Abaigar et al.(2024) argument that governance frameworks in developing economies can simultaneously constrain low capability organizations and enable high capability ones.

Similarly, Ghana's high mobile penetration creates latent data collection opportunities, for real-time customer feedback, transactional analytics, and geospatial intelligence, that organizations at Stages 3 and 4 are beginning to exploit. However, unreliable power supply, limited server infrastructure outside Accra, and thin broadband connectivity outside urban centres constrain the scalability of these opportunities. These findings extend Avgerou's (2008) socio-technical analysis of IS in developing

countries by demonstrating that infrastructure is not merely an enabling or disabling factor but a dynamic moderator whose effects vary systematically with organizational maturity.

5.5 The Barrier Hierarchy and the Case for Staged Interventions

The hierarchical structure of DDDM barriers identified in this study, foundational data quality issues cascading into human capital deficits, which are compounded by technological and financial constraints, which are further complicated by structural and environmental headwinds, has direct implications for intervention design. Consistent with socio-technical systems theory (Bostrom & Heinen, 1977), sustainable DDDM adoption requires joint optimization of social (human capital, culture, governance) and technical (infrastructure, tools) subsystems. Interventions that address only one subsystem will fail: investing in advanced analytics tools without simultaneously building data governance capacity and analytical culture produces expensive underutilization. Conversely, building data literacy without providing the infrastructure to put those skills to use produces frustration and talent attrition.

These findings suggest that maturity aware, staged intervention roadmaps are more effective than technology-first strategies. Organizations at Stage 1 should prioritize data quality improvement and governance framework design before investing in BI tools. Those at Stage 2 should focus on embedding analytical outputs into management decision rhythms before scaling to advanced analytics. Those at Stage 3 should invest in cross system data integration and specialized analytical talent before pursuing AI-driven automation. This staged logic respects the hierarchical nature of the barrier structure and avoids the "technology fallacy" that Heeks (2002) identifies as a primary driver of IS initiative failure in developing economies.

5.6 Practical Implications

For organizational managers, the study recommends three priority actions. First, conduct a DDDM maturity diagnostic, using instruments such as the DECAS model (Elgendy et al., 2024) or the TDWI maturity assessment, before committing to technology investments, so that investment priorities match the organization's actual capability baseline. Second, redesign management meeting structures to embed systematic data review, because this single organizational routine, consistently demonstrated by higher maturity organizations, drives cultural change more effectively than standalone training programmes. Third, treat data governance and cybersecurity compliance with Ghana's Data Protection Act not as a cost centre but as a VRIN resource building investment that signals trustworthiness to clients, partners, and regulators.

For policymakers and development partners, the study recommends four national ecosystem actions: establish a Ghana Data Quality Standards Framework that sets baseline data interoperability requirements for public institutions; create a national DDDM maturity assessment programme for public sector organizations, linked to performance incentives; fund sector level data literacy programmes through public private partnerships between national universities and technology sector companies; and

develop regulatory sandboxes that allow organizations to experiment with AI-driven analytics in controlled environments before full deployment, reducing the risk premium currently attached to advanced analytics investment.

6. Limitations and Future Research

6.1 Limitations

This study is subject to five limitations that should inform interpretation of its findings. First, the qualitative design with 30 participants, while sufficient to achieve thematic saturation (Guest et al., 2006), does not support statistical generalization. The findings represent a theoretically transferable account of DDDM practices in Ghanaian formal sector organizations rather than a statistically representative national survey. Second, purposive sampling through a single institutional professional network produced a sample skewed toward urban, formally educated, and relatively resource advantaged organizations. Rural organizations, informal sector businesses, and organizations in non-capital cities are underrepresented, limiting the study's ability to speak to DDDM challenges in these contexts. Third, reliance on self-reported interview data introduces the possibility of social desirability bias: participants may have overstated their organizations' DDDM sophistication. The study did not triangulate interview accounts against objective performance metrics or organizational records. Fourth, the cross-sectional design captures a single moment in a rapidly evolving landscape; longitudinal research would be needed to track maturity progression and capability building trajectories over time. Fifth, the operationalization of VRIN criteria in this study is theory driven and post-hoc rather than based on pre-specified measurement scales, limiting comparability with prior RBV research. Future studies should develop validated VRIN scales specific to the DDDM context.

6.2 Future Research Directions

This study opens four priority avenues for future research. First, large scale quantitative surveys using validated DDDM maturity scales and VRIN measurement instruments would allow statistical testing of the framework's predictive validity and enable comparison across national contexts. Second, longitudinal case studies tracking individual organizations through maturity transitions, ideally following organizations that receive targeted DDDM capability investments, would provide empirical evidence of the sensing seizing reconfiguring logic of dynamic capabilities in practice. Third, comparative studies across West African contexts, Nigeria, Côte d'Ivoire, Senegal, would disentangle Ghana specific contingencies from regional patterns, enabling more generalizable theory about DDDM adoption in Sub-Saharan Africa. Fourth, action research designs that co-design and pilot decision-centric analytics tools (MCDA dashboards, AutoML with human oversight, explainable AI) with Ghanaian organizations would generate both practical artefacts and theoretical insights about how context shapes technology organization fit.

Additionally, research on data governance and algorithmic accountability in Ghana specifically should examine how the Ghana Data Protection Act (2012) is operationalized in practice, where compliance

gaps exist, and how emerging AI applications, particularly in lending and public service delivery, can be governed to prevent algorithmic bias and protect citizen rights (Fischer-Abaigar et al., 2024; Mahroof et al., 2025).

7. Conclusions

This study examined the emergence, operationalization, and differentiation of data-driven decision-making (DDDM) in Ghanaian organizations through 30 qualitative interviews across eight sectors. Three findings stand out as primary contributions. First, Ghanaian organizations operate along a four stage DDDM maturity continuum broadly consistent with established global models but with a distribution heavily weighted toward Stages 1 and 2. This is a reflection of Ghana specific infrastructural, human capital, and governance constraints rather than a lack of organizational aspiration. Second, maturity is not primarily a function of organizational size or sector: positive deviant organizations achieve higher than expected maturity through VRIN capability bundles, combinations of leadership commitment, data governance routines, and analytical culture, that competitors cannot easily replicate. Third, barriers form a hierarchical chain in which foundational data quality failures cascade into human capital and technological deficits, suggesting that staged, socio-technically integrated intervention strategies are more effective than technology-first approaches.

The hybrid TOE-RBV framework, augmented by dynamic capabilities theory, proved analytically productive across all six research questions. It explains why adoption pressures exist (TOE environmental conditions), why similar pressures produce differential outcomes (RBV VRIN resources), and how organizations can deliberately build maturity over time (sensing-seizing-reconfiguring dynamic capabilities). By operationalizing VRIN criteria in the DDDM domain and applying them to a developing economy context, this study extends both RBV and TOE scholarship and demonstrates the value of theory hybrid approaches in IS adoption research.

Ghana's DDDM transformation is underway but uneven. Its success depends on a three pillar strategy: building human capital and analytical culture as the primary investment; strengthening data foundations, quality, governance, and security, as the enabling infrastructure; and establishing a supportive national ecosystem of policy, regulation, and public private partnership as the systemic context. Organizations and policymakers that pursue these three pillars concurrently, and that calibrate their investments to their current maturity stage, are best positioned to realize the productivity and governance benefits that data-driven decision-making promises.

Declarations

All authors read and approved the final manuscript.

Ethics approval and consent to participate

Ethical approval for this study was granted by the Institutional Ethics Committee of the Ghana Institute of Management and Public Administration (GIMPA) prior to data collection. All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments. Participation was voluntary, and written informed consent was obtained from all participants prior to the interviews. Participants were informed of their right to withdraw at any time without consequence. All organizational and individual identifiers were anonymized to protect confidentiality.

Consent for publication

Not applicable. This manuscript does not contain any individual person's data in any form (including individual details, images, or videos). All data presented are aggregated and anonymized at the organizational level, and no identifiable information about specific individuals is included. Participants were informed that anonymized findings would be published in academic outlets.

Competing interests

The authors declare that they have no competing interests. No financial or non-financial interests that could have influenced the research, analysis, or interpretation of the findings exist. All authors have no relationships or activities that could appear to have influenced the submitted work.

Alfred Nyadroh

Conceptualization, Methodology, Investigation, Formal analysis, Writing – Original Draft, Writing – Review & Editing, Project administration.

Joseph Budu

Conceptualization, Methodology, Investigation, Formal analysis, Writing – Review & Editing, Supervision.

Emmanuel Antwi-Boasiko

Investigation, Formal analysis, Writing – Original Draft, Data curation.

Elizabeth Addy

Investigation, Formal analysis, Writing – Original Draft, Visualization.

Felicia Engmann

Investigation, Formal analysis, Writing – Review & Editing, Visualization.

Emmanuel Adabor

Investigation, Formal analysis, Writing – Review & Editing, Data curation.

Isaac Wiafe

Conceptualization, Methodology, Formal analysis, Writing – Review & Editing, Supervision.

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Availability of data and material

The datasets generated and analyzed during the current study are not publicly available due to the sensitive nature of the interview data and the confidentiality agreements with participating organizations. Participants were assured that raw data would remain confidential and accessible only to the research team. Anonymized excerpts from the interviews are presented in the manuscript to support the findings. The corresponding author may be contacted for reasonable requests regarding the data, subject to institutional ethics approval and participant consent conditions.

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Figures

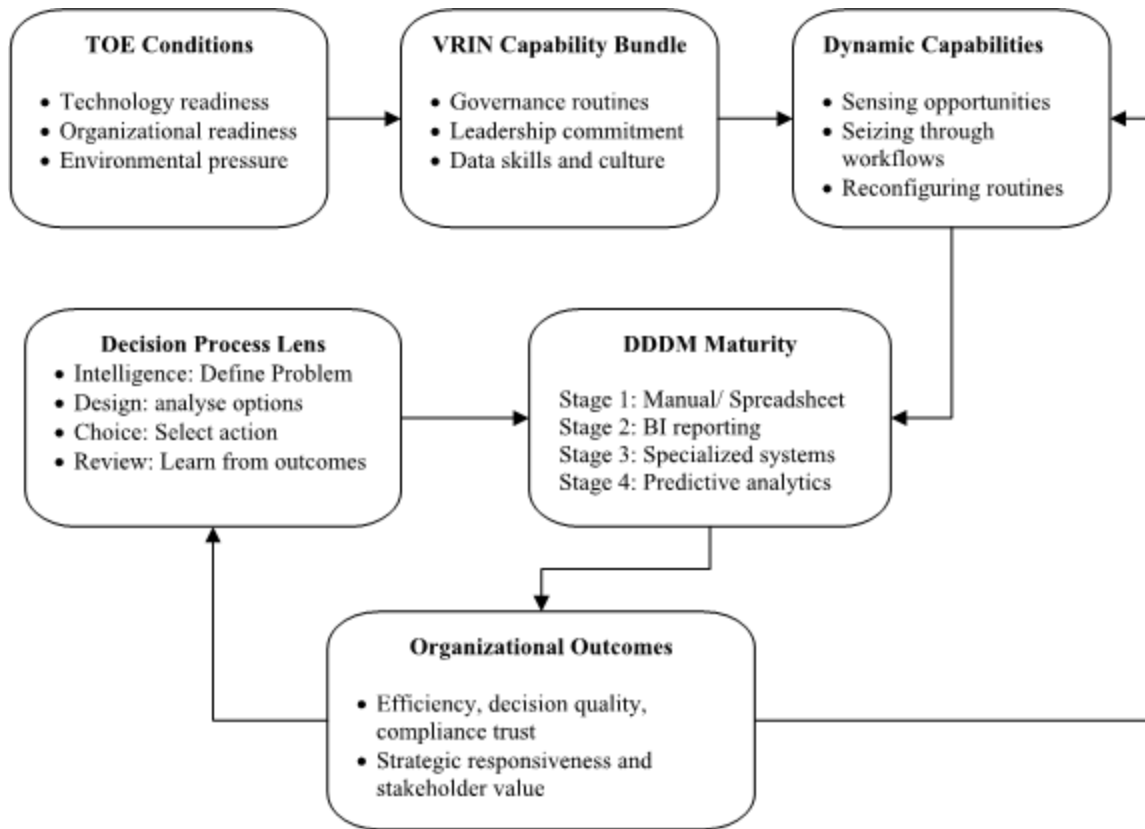


Figure 1

TOE-RBV Dynamic Capability Framework