DIGITAL TRANSFORMATION, INTERDISCIPLINARY APPLICATIONS AND SOCIETAL IMPACT

DATA-DRIVEN DECISION MAKING IN DIGITAL BUSINESSES: TOOLS, LIMITS, AND MANAGERIAL IMPLICATIONS

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Abstract. ing a process-based conceptual approach, the study examines how data moves from collection to decision, identifying key bottlenecks and quality-degradation mechanisms at each stage transition. Particular attention is given to two critical failure points: the data quality gap at the transition from infrastructure to analytics, and the illusion of objectivity at the handoff from automated outputs to managerial judgment. The analysis yields three principal contributions: a three-layer process model mapping the structurThe proliferation of digital analytics tools has fundamentally altered how organisations collect, process, and act on data. Yet the relationship between data availability and decision quality remains poorly understood: despite substantial investment in data infrastructure and analytical platforms, a large share of organisations report persistent distrust in the data they use for strategic decisions, and measurable losses attributable to poor data quality continue to mount. This paper argues that the gap between tool deployment and decision improvement is structural, not incidental, and develops a process-based conceptual model designed to make that structure analytically visible. The model integrates three core components - data infrastructure, analytical tools, and managerial interpretation - into a sequential flow grounded in the DIKW hierarchy and bounded rationality theory. Usal components of DDDM in digital businesses; a bottleneck taxonomy covering nine distinct risk mechanisms with explicit severity criteria; and a formalised Decision Quality function capturing the multiplicative interdependence of the three layers. The paper contributes to the literature by shifting focus from tool capabilities to the decision logic those tools are meant to support, and offers a diagnostic framework for practitioners seeking to improve decision effectiveness in data-rich environments.

Keywords: data-driven decision-making, digital business, analytical tools, managerial interpretation, algorithmic bias, decision quality

JEL Classification: M15, O33, D81

INTRODUCTION

The pace at which digital businesses accumulate data has outrun their capacity to act on it. The global data analytics market reached USD 69.54 billion in 2024 and is projected to grow at a compound annual rate of 28.7% through 2030 (Grand View Research, 2025), reflecting unprecedented investment in tools, platforms, and infrastructure that promise to make decision-making faster, more accurate, and less dependent on managerial intuition. Yet the returns on this investment remain paradoxical. While 76% of organisations report data-driven decision-making as a top goal for their data programmes, 67% still do not completely trust the data they rely on for those decisions (Precisely and Drexel LeBow College of Business, 2024). Over a quarter of organisations estimate they lose more than USD 5 million annually due to poor data quality, and 43% of chief operations officers identify data quality as their most significant data priority (IBM Institute for

Business Value, 2025). These figures point to a fundamental gap: investment in data tools has not translated proportionally into decision quality.

What makes this gap difficult to close is that it does not show up in the technical infrastructure. Organisations have more dashboards, more machine learning pipelines, and more automated recommendation engines than at any point in history. The problem runs deeper: the logic by which this machinery is supposed to improve decisions has never been made sufficiently explicit. Existing research has moved in two fairly separate directions - one focused on the organisational conditions that enable data-driven cultures (Davenport and Harris, 2017; Szukits and Móricz, 2024), the other on the specific failures that tools generate, from algorithmic bias to information overload (Engin and Treleaven, 2019; Pittenger *et al*., 2023). What neither stream provides is a unified process model that traces how data moves from collection to decision, identifies where quality is lost at each transition, and specifies what role managerial judgment plays in recovering or compounding that loss.

This paper develops such a model. The central argument is that data-driven decision-making in digital businesses is best understood not as a capability to be built, but as a process to be managed - one with three structurally distinct layers (data infrastructure, analytical tools, and managerial interpretation) and at least two critical transition points where quality degradation becomes systematic. The model draws on the DIKW (Data-Information-Knowledge-Wisdom) hierarchy (Ackoff, 1989; Rowley, 2007), bounded rationality theory (Simon, 1997), and recent empirical work on algorithmic bias and data governance to construct a coherent explanatory architecture.

The study addresses three research questions. First: what are the structural components of a process-based model of DDDM (Data-Driven Decision-Making) in digital businesses? Second: at which transition points does decision quality degrade, and through what mechanisms? Third: what are the managerial implications of this model for improving decision effectiveness in practice?

The paper is organised around these questions. The literature review in Section 2 traces how the field arrived at its current impasse, identifying the gaps that the model is designed to fill. Section 3 explains the methodological choices that underpin a conceptual study of this kind. Section 4 presents the model in full, including the bottleneck taxonomy and the Decision Quality function. Section 5 translates the model into a practical diagnostic for managers, and Section 6 closes with conclusions and directions for future research.

LITERATURE REVIEW

1. From intuition to analytics: the first wave of literature

The intellectual foundation of the DDDM field was laid by two converging traditions. The first is the management analytics literature, most influentially articulated by Davenport and Harris (2017), who argued that the frontier for using data to make decisions has shifted dramatically, with high-performing enterprises building competitive strategies around data-driven insights. This position was reinforced by McAfee and Brynjolfsson (2012), who claimed that big data allows managers to know radically more about their businesses and directly translate that knowledge into improved decision making and performance. Taken together, this first wave of literature established a compelling narrative: data availability equals decision quality - a framing that shaped an entire generation of digital transformation strategies.

The second tradition is the information systems literature on decision support, rooted in Herbert Simon's (1997) concept of bounded rationality. Simon argued that decision-makers operate under cognitive constraints - limited time, attention, and computational capacity - and therefore satisfice

rather than optimise. This framing positioned data tools as a means to extend rationality by reducing those constraints. What remained underspecified was whether better data access actually narrows the bounds of managerial rationality, or simply relocates them.

2. The capability turn: what organisations need to be data-driven

A second wave of literature shifted focus from data access to organisational capability. Vidgen, Shaw and Grant (2017) proposed that data-driven decision-making requires technical, human, and organisational dimensions - making the important point that analytics tools are necessary but not sufficient conditions for improved decisions. Drawing on a survey of 305 medium-sized and large companies, Szukits and Móricz (2024) demonstrated that top management support for business analytics and perceived data quality are strong predictors of an analytical decision-making culture, and that analytical culture increases centralisation of data use - yet such centralisation does not automatically translate into data-driven decisions without supporting organisational routines.

This line of inquiry produced a rich set of enablers - leadership commitment, data literacy, change management, and cross-functional data governance - but tended to treat them as additive factors rather than examining their interactions within a process logic. The capability approach answered the question "what do organisations need?" without fully addressing "where in the decision process does capability matter?"

3. The dark side debate: limits, biases, and objectivity illusions

A third and more critical strand of literature emerged in parallel, questioning whether the optimistic narrative of the first wave was adequately qualified. Three specific challenges have received sustained attention. The first is algorithmic bias. Engin and Treleaven (2019) identify three major sources - data bias, method bias, and societal bias - and demonstrate that dynamic managerial capabilities are required to address them. These biases are particularly insidious because they operate within the analytical layer while appearing as neutral technical outputs. AI systems that use biased results as input data create a feedback loop that reinforces bias over time (IBM, 2026).

The second challenge is information overload. Bakshy, Messing and Adamic (2015) show how algorithmic curation shapes exposure to information in social media environments, demonstrating that automated ranking systems can systematically filter what users see in ways that reinforce pre-existing patterns. By analogy, similar filtering and prioritisation mechanisms may affect managerial dashboards when automated systems determine which metrics and alerts are made visible - amplifying certain signals while suppressing others without the manager’s awareness. The proliferation of automated alerts and BI metrics increases cognitive load without proportionally improving signal quality. The third challenge is the illusion of objectivity: the tendency of automated outputs to be perceived as factual rather than inferential. Engin and Treleaven (2019) note that the technology industry's framing of decision-making tools as efficient and objective tends to suppress critical evaluation in ways that are difficult to detect through normal management practice.

4. Theoretical contribution and the gap this paper addresses

Despite the richness of these three streams, the literature shares a structural limitation: it analyses infrastructure quality, tool performance, and managerial cognition as separate research objects, studied in isolation by different scholarly communities. Infrastructure research is largely technical; the capability literature is organisational; the bias literature sits at the intersection of computer science and ethics. What is missing is a framework that situates all three within a single process logic - one that makes visible how failure at any stage propagates to the decision outcome.

The model proposed in this paper is designed to work precisely in that space between the three streams. It takes the DIKW hierarchy (Ackoff, 1989; Rowley, 2007) as a useful starting scaffold, but extends it by filling in what the hierarchy leaves blank: the organisational and cognitive work required at each stage of the data-to-decision journey. It takes Simon's (1997) bounded rationality seriously, but goes beyond the general claim that managers satisfice by locating specific, structurally predictable failure modes at identifiable transition points. And it takes the capability literature (Vidgen, Shaw and Grant, 2017; Szukits and Móricz, 2024) seriously as well, while arguing that the factors it identifies are not independent levers that can be adjusted separately, but components of a system whose output depends on how well they fit together. Where the DECAS model (Elgendy, Elragal and Päivärinta, 2022) addresses these questions at the level of decision theory, the present paper addresses them at the level of process architecture - at the point where abstract frameworks meet the practical question of what goes wrong and why.

MATERIALS AND METHODS

This paper adopts a process-based conceptual approach, combining theoretical framework development with a structured synthesis of existing literature. Conceptual modelling is the appropriate research design when the objective is to clarify the underlying logic of a phenomenon rather than measure its empirical distribution. The study's contribution lies in the logical architecture of the model and its capacity to reorganise existing knowledge into a coherent explanatory structure.

The literature synthesis was conducted through systematic searches of Scopus, Web of Science, ScienceDirect, Emerald Insight, and Springer Link. The primary search terms were: "data-driven decision-making", "business analytics", "data quality", "algorithmic bias", "managerial judgment", "bounded rationality", and "decision quality". Secondary searches combined these terms with "digital business", "data infrastructure", "information overload", and "automation bias". The analysis covered publications from 2012 to 2025, with exceptions for foundational works (Ackoff, 1989; Simon, 1997; Weick, 1995). Inclusion criteria prioritised peer-reviewed articles in management, information systems, and decision science journals; exclusion criteria eliminated conference abstracts without full text, and literature reviews that did not report primary data or original conceptual frameworks. Commercial reports were used exclusively for contextualisation in the Introduction and were not used to support theoretical propositions.

The three layers of the model - data infrastructure, analytical tools, and managerial interpretation - emerged from a convergent reading of the three literature streams identified in Section 2: the data availability tradition, the capability turn, and the limits critique. Each stream maps onto one layer of the model, and the bottleneck hypotheses derive from the transition points between streams that the existing literature identifies but does not integrate. The process-based framing draws on Vidgen, Shaw and Grant (2017) and applies it at a finer grain of analysis.

The model itself is built from the literature outward rather than from observations inward. Theoretical premises drawn from the three streams identified in Section 2 provide the foundation; the bottleneck hypotheses and managerial implications follow by logical derivation. The test of validity, at this stage, is not statistical fit but coherence: whether the model's internal logic holds together and whether its claims align with what the reviewed studies have found empirically. The limitations of this approach are genuine and are addressed directly in the Conclusions section.

RESULTS AND DISCUSSION

1. The proposed process model

The model proposed here follows a simple premise: a decision cannot be better than the data it rests on, but good data is not sufficient to produce a good decision. Between raw data and managerial action lie two further layers - the analytical tools that process it, and the interpretive work that a manager must do to make sense of what those tools produce. Figure 1 represents this as a three-layer process flow. Each layer has its own actors, its own internal logic, and, critically, its own characteristic failure modes. The interest of the model lies less in the layers themselves than in what happens at the junctions between them, where the failures of one layer silently enter the next. This is where capability-based accounts tend to lose analytical precision: they tell us what organisations need, but not where in the sequence things go wrong. The DIKW hierarchy (Ackoff, 1989; Rowley, 2007) is a useful reference for the direction of travel - from data through information and knowledge to actionable wisdom - but says little about the organisational conditions that make each step possible or likely to fail. The model fills in that gap.

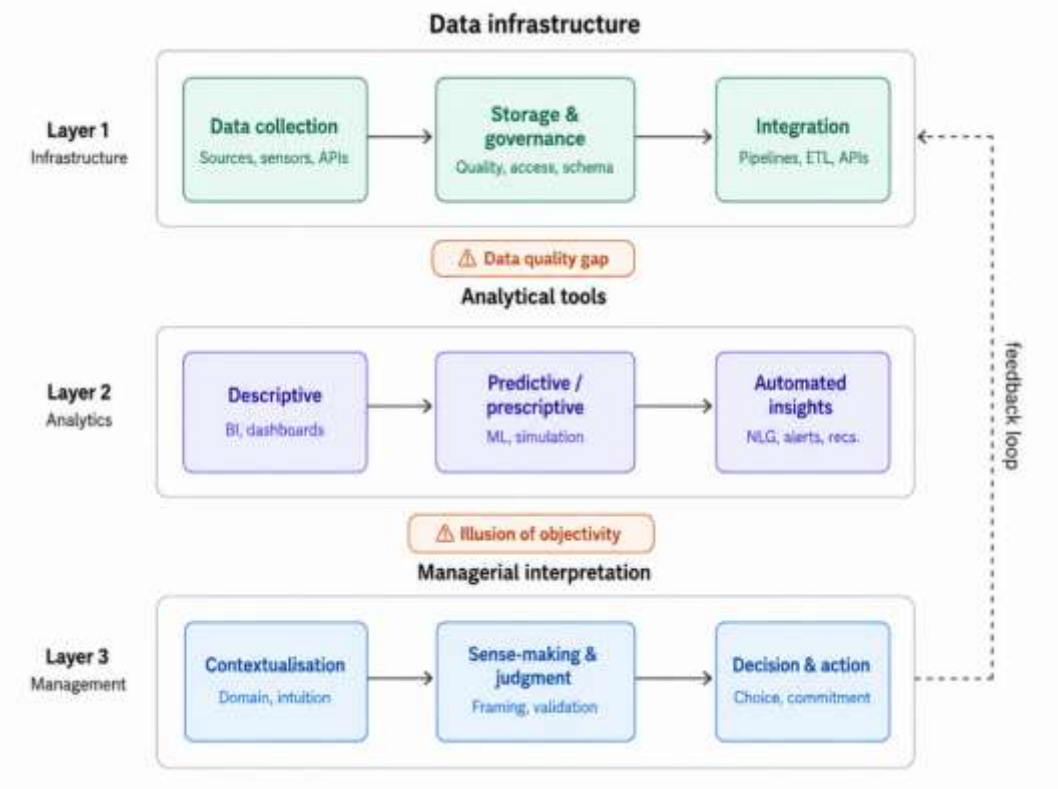


Figure 1. Three-Layer Process Model of Data-Driven Decision-Making in Digital Businesses
Source: *Authors' own elaboration.*

2. Layer 1 – Data infrastructure

The first layer encompasses data collection, storage and governance, and integration. Infrastructure quality (*Iq*) determines the epistemic foundation on which all subsequent layers rest. When this foundation is compromised - through biased sampling, inconsistent schemas, or silent ETL errors - analytical outputs inherit those flaws and carry them into the decision, often invisibly. Industry analysis of over 1,000 data pipelines suggests that 72% of quality issues are detected only after they have already influenced business decisions (Datachecks, 2024) - a figure that, while not from a peer-reviewed source, is consistent with the broader literature on data quality management, which

consistently identifies late detection as a primary characteristic of infrastructure-level failures (Vidgen, Shaw and Grant, 2017). The model identifies the transition from Layer 1 to Layer 2 as the first critical bottleneck: the data quality gap (Table 1). Unlike tool-level failures, infrastructure failures are structurally upstream and cannot be corrected by more sophisticated analytics downstream.

3. Layer 2 – Analytical tools

The second layer covers descriptive analytics (BI, dashboards), predictive and prescriptive models (machine learning, simulation), and automated insight generation (NLG, recommendation engines). Tool effectiveness (*T*e) is not a binary property but a function of fit-to-purpose: a well-calibrated predictive model is highly effective for a specific problem domain and misleading when applied outside it. Three failure modes are characteristic of this layer. Algorithmic bias is the most studied: when training data carries the imprints of historical inequities or measurement errors, the models built on it reproduce and often amplify those distortions, while presenting their outputs in a form that reads as neutral analysis (Engin and Treleaven, 2019). The self-reinforcing dynamic is well documented - biased outputs fed back as inputs accelerate rather than correct the problem (IBM, 2026). Less well studied but equally consequential is metric overload: as the number of active dashboards and KPI streams grows, managers face an environment in which the cognitive work of identifying meaningful signals from noise becomes the limiting constraint on decision quality, regardless of how good the underlying data is (Bakshy, Messing and Adamic, 2015). The third failure mode - what this paper calls the illusion of objectivity - is perhaps the most structurally dangerous: automated insight tools, particularly natural language generation systems, present inferences as facts. A recommendation phrased in declarative language carries a different epistemic weight than the same recommendation presented as a probabilistic estimate with stated assumptions, and that weight tends to suppress rather than invite the critical scrutiny that good judgment requires. This is the hinge point of the second critical bottleneck.

4. Layer 3 – Managerial interpretation

The third layer - contextualisation, sense-making and judgment, and decision and action - is where data-driven logic meets organisational reality. Managerial competence (*M*c) refers specifically to the capacity to receive analytical outputs critically, to supply contextual knowledge that tools cannot access, and to exercise sense-making: the retrospective construction of meaning from ambiguous signals (Weick, 1995). Research confirms that while data is omnipresent in contemporary management, data quality, utility, and value remain inconsistent, and satisficing behaviours persist even in the age of data-at-your-fingertips (Pittenger *et al*., 2023). This finding has a counterintuitive implication: data abundance does not eliminate bounded rationality (Simon, 1997); it reshapes it. Managers now satisfice not from lack of data but from inability to evaluate data critically under time pressure.

5. Bottleneck analysis and severity framework

Table 1 presents a systematic analysis of nine bottleneck and risk mechanisms across the three layers. Severity levels are assigned on the basis of four criteria: (1) impact on decision outcome - the degree to which the risk distorts the final decision; (2) probability of occurrence - how frequently the condition arises in digital business contexts, based on the reviewed literature; (3) detectability - the ease with which the risk can be identified before it reaches the decision; and (4) reversibility - whether the failure can be corrected without structural investment. This multi-criteria framing ensures that severity labels are grounded in explicitly stated logic rather than subjective judgment.

Table 1. Bottleneck and Risk Analysis Across the Three Layers of the DDDM Process Model

Layer	Stage	Bottleneck / risk	Mechanism	Severity criteria
L1	Data collection	Incomplete or biased sampling	Structural gaps propagate downstream and cannot be corrected at later stages	High impact; high probability; low detectability before decision
L1	Storage & governance	Inconsistent schema; poor data lineage	Integration failures reduce analytical reliability at source	High impact; medium probability; reversible only with governance investment
L1	Integration (ETL)	Latency; silent transformation errors	Stale or corrupted data reaches analytics layer undetected	Medium impact; medium probability; moderate detectability
L2	Descriptive analytics	Dashboard overload; metric proliferation	Cognitive load prevents meaningful signal extraction by managers	Medium impact; high probability in mature BI environments; partially reversible
L2	Predictive / prescriptive	Algorithmic bias; overfitting to historical patterns	Model outputs systematically misrepresent future states; bias reinforces over time	High impact; medium probability; low detectability without model audit
L2	Automated insights	Illusion of objectivity in NLG outputs	Framing effects suppress critical managerial evaluation of algorithmic outputs	High impact; high probability; accountability diffuses to algorithm
L3	Contextualisation	Automation bias; over-reliance on recommendations	Managerial judgment displaced rather than augmented by tool outputs	High impact; high probability; undermines strategic responsibility
L3	Sense-making & judgment	Satisficing under data abundance	Data availability does not eliminate bounded rationality under time pressure	Medium impact; high probability; partially reversible via training
L3	Decision & action	Accountability diffusion in algorithm-assisted choices	Unclear human–machine attribution weakens decision ownership and responsibility	Emerging impact; low probability currently; increasing as automation deepens

Source: *Authors' synthesis based on Pittenger et al. (2023); Engin and Treleaven (2019); Davenport and Harris (2017); Simon (1997); Bakshy, Messing and Adamic (2015).*

6. The Decision Quality function

The relationships identified in the preceding sections can be brought together in a single function that captures how the three layers jointly determine decision quality. The formulation is intended as a structural argument, not a measurement tool:

$$\mathbf{DQ = f(Iq, Te, Mc) - \Sigma Ri} \quad \mathbf{(1)}$$

In expanded form:

$$\mathbf{DQ = \alpha \cdot Iq \cdot Te \cdot Mc - \beta \cdot Rbias - \gamma \cdot Roverload - \delta \cdot Robj} \quad \mathbf{(2)}$$

Where *DQ* = Decision Quality; *I*q = Infrastructure quality (0-1); *T*e = Tool effectiveness (0-1); *M*c = Managerial competence (0-1); and *R*bias, *R*overload, *R*obj = conditional risk penalties activated when specific parameter thresholds are breached. The coefficients α, β, γ, and δ are treated as heuristic weights in the current version of the model - they reflect the relative order of magnitude of each component's contribution as inferred from the reviewed literature, but have not been empirically calibrated. Future research should operationalise these coefficients through expert scoring, Delphi consultation, or survey-based measurement across organisational contexts. This transparency is essential: the function's contribution at this stage is structural rather than quantitative, and any future empirical use would require sector-specific calibration.

The choice of a multiplicative rather than additive form is deliberate. Additive models imply that a strength in one area can offset a weakness in another; multiplication does not. A high-performing analytical layer cannot compensate for corrupted infrastructure, and skilled management cannot rescue insights built on biased models. The three factors are complements, and the function reflects that. Three organisational scenarios illustrate the practical significance of this claim. In the first scenario, an organisation with strong infrastructure and capable management deploys limited analytical tools: the binding constraint is *T*e, and DQ remains moderate regardless of the quality of the other two layers. In the second scenario, a digitally mature organisation invests heavily in predictive analytics but data governance is fragmented: even a high-performing analytical layer cannot recover what infrastructure corrupts upstream - the *R*bias penalty is structurally embedded (Davenport and Harris, 2017). In the third scenario, both infrastructure and tools are well-developed but managerial competence in interpreting outputs remains low: high *T*e combined with low *M*c activates the *R*obj penalty, as managers default to algorithmic recommendations as if they were objective facts. Across all three scenarios, the diagnostic implication is the same: improving DQ requires identifying the binding constraint and addressing it through coordinated investment across all three layers.

7. Managerial implications

A model that cannot be used is a model that has not done its job. The decision-logic gap is not visible in ROI metrics on technology investment: an organisation can spend heavily on a BI platform, report high system utilisation, and still be making worse decisions than before, because the binding constraint was never the tooling. Identifying where the real problem lies requires a different kind of audit - one that moves through the process layer by layer. The questions below are designed to support that audit.

For Layer 1 (Data infrastructure): Are data sources documented and their coverage gaps known? Is there a data governance policy that defines ownership, quality standards, and lineage? Are ETL pipeline errors logged and reviewed before analytical runs? A negative answer to any of these questions indicates that *I*q is likely the binding constraint, and that investment in analytical tools will yield limited returns until infrastructure is stabilised.

For Layer 2 (Analytical tools): Are predictive models tested for bias before deployment? Is the number of active dashboards and KPIs reviewed periodically for cognitive load? Are automated recommendations presented with confidence intervals or uncertainty ranges that preserve managerial judgment? Organisations that score poorly on these criteria face *T*e limitations combined with active *R*bias or *R*overload penalties.

For Layer 3 (Managerial interpretation): Do managers have formal training in data literacy and critical evaluation of algorithmic outputs? Are there institutional routines - devil's advocate processes, pre-mortems, or mandatory challenge periods - that require explicit justification before data-driven recommendations are adopted? Is decision accountability clearly assigned to a named individual rather than diffused to "the model"? Low scores here indicate that *M*c is the binding constraint, and that further investment in infrastructure or tools will not translate into improved decisions.

These three diagnostic clusters correspond directly to the bottleneck taxonomy in Table 1. The practical value of the model lies precisely in this mapping: by identifying which layer fails first, managers can prioritise interventions that address root causes rather than symptoms. An organisation that replaces its BI platform because dashboards are not trusted, when the real problem is poor data governance at Layer 1, will reproduce the same failure at a higher cost.

8. Key finding: the decision-logic gap

Running through each of the sections above is a single diagnostic observation, which this paper calls the decision-logic gap. Organisations invest in data tools with the goal of improving decisions, yet the logic connecting tools to decisions has typically not been made explicit. The gap emerges precisely because tool deployment is optimised for data availability and processing speed, while decision improvement depends on something different: the integration of analytical outputs with contextual judgment that only a manager can supply. Szukits and Móricz (2024) find empirically that developing an analytical culture and centralising data use does not automatically produce better decision-making - a result the model explains readily: centralisation strengthens the infrastructure and analytical layers, but cannot reach *Mc* deficiencies at Layer 3. The proposed model directly addresses this gap by making each transition point - and its associated risk - analytically visible, providing a framework that practitioners can apply without requiring proprietary data or specialised measurement instruments.

CONCLUSIONS

The problem this paper started from - that organisations invest heavily in data tools without achieving proportional improvements in decision quality - is not hard to observe, but it has proved difficult to explain precisely. The framework developed here offers one explanation: the gap is structural, and it appears at predictable points in the journey from data to decision. Two junctures stand out. At the transition from infrastructure to analytics, quality failures that accumulated upstream enter the analytical layer undetected, shaping outputs before any manager has a chance to intervene. At the transition from automated outputs to managerial judgment, the framing conventions of algorithmic tools tend to substitute for the critical interpretation they were supposed to support.

The most practically consequential finding concerns the nature of the relationship between the three layers. They are not independent levers. An organisation that treats infrastructure investment, analytical tooling, and management training as separate line items - to be addressed in sequence or traded off against each other - will not get the improvements it expects, because the three factors interact multiplicatively rather than additively. Neglecting data governance while upgrading analytical platforms, or deploying machine learning models while leaving managers without the training to challenge their outputs, reproduces the same structural failure at higher cost. This is a direct implication of the Decision Quality function, and it runs counter to the way digital transformation programmes typically present the problem.

The analysis of Layer 3 also pushes back against a quieter assumption embedded in much of the DDDM literature: that better tools eventually reduce the need for human judgment. The evidence reviewed here suggests the opposite. Managers satisfice not because they lack data but because they face predictable cognitive pressures that data abundance does not relieve (Pittenger *et al*., 2023; Simon, 1997). The model makes this concrete: the binding failure mode is not that managers ignore data, but that they face structurally predictable conditions - automation bias, objectivity illusion, accountability diffusion - at the point where analytical outputs enter their interpretive frames.

Perhaps the most useful thing about the decision-logic gap as a concept is that it is diagnosable. Identifying which layer is the binding constraint in a given organisation does not require proprietary data or specialised instrumentation - it requires a structured audit of the kind outlined in Section 4.7. That auditability is deliberate: the model is designed to be applied, not just cited.

The framework developed here comes with genuine constraints that future research will need to address. The model has not been tested against empirical data: the bottleneck taxonomy and

severity assignments rest on a reading of existing literature, not on primary observation, and may reflect the biases of that literature. The coefficients in the Decision Quality function are heuristic placeholders rather than calibrated estimates; they give the function structural meaning, but any quantitative application would require sector-specific calibration through expert elicitation or survey-based measurement. The model also treats digital businesses as a relatively homogeneous category, which they are not. The infrastructure challenges facing a data-native platform business are different in kind from those of a manufacturing firm mid-way through digital transition, and the model says nothing about how the bottlenecks distribute differently across operational, tactical, and strategic decision contexts - a distinction that matters. Similarly, resource constraints in smaller organisations are likely to affect Layer 1 and Layer 3 far more severely than they affect large corporations, yet the model does not capture this asymmetry. Resolving these gaps would require moving from conceptual framework to empirical programme: operationalising *I*q, *T*e, and *M*c as measurable indices that allow comparative analysis across organisational contexts. What the model contributes at this stage is a process logic precise enough to be tested - a starting point, not an end point.

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