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Beyond Big Data: A Multi-Dimensional Framework for Understanding Business Decision Failure in the Era of Artificial Intelligence

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Abstract

This study has examined why organizations that are rich in data and equipped with advanced analytics and artificial intelligence continue to make poor business decisions, and it has developed and tested a multi-dimensional framework for understanding business decision failure in the era of artificial intelligence. The central puzzle motivating the study has been that access to large volumes of data and to sophisticated models has not, in itself, guaranteed good decisions, because failure arises not from a single deficiency but from the interaction of technical, organizational, and human factors that a purely data-centric view overlooks. Guided by three research questions, why data-driven organizations still make poor decisions, what organizational, technical, and human factors contribute to failure, and how businesses can prevent these failures, the study has proposed a framework comprising five contributing dimensions: data quality, integration and governance; model validity, interpretability and fit-for-purpose; organizational decision culture and accountability; human cognition, judgment and bias; and governance, oversight and error-correction, with decision quality as the outcome. A quantitative, cross-sectional design has been used, and data have been collected from managers, analysts, data scientists, and decision-makers across a range of industries. Out of 289 distributed questionnaires, 246 valid responses have been retained, producing an 85.1% valid response rate. The analysis has included descriptive statistics, reliability testing, correlation analysis, multiple regression, and an analysis of the contribution and severity of failure modes drawn from respondents' reported decision-failure cases. The findings have shown that all five dimensions were significantly and positively associated with decision quality, that the regression model was significant, $F(5, 240) = 50.19$, $p < .001$, explaining 51.1% of the variance, and that data quality, integration and governance and model validity, interpretability and fit-for-purpose were the strongest statistical predictors, while organizational and human factors were the most frequently cited and among the most severe contributors in reported failure cases. The study concludes that decision failure in data-rich organizations is a socio-technical rather than a purely technical phenomenon, and that its prevention requires the joint strengthening of data and model quality, decision culture and accountability, debiasing of human judgment, and governance and error-correction, rather than the accumulation of more data alone.

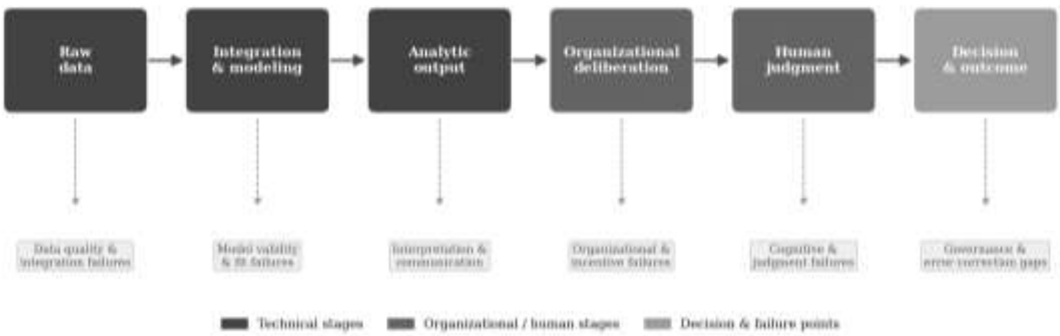
Keywords
Business Decision Failure; Data-Driven Decision-Making; Artificial Intelligence; Decision Quality; Organizational Decision Culture; Cognitive Bias; Data Governance.

INTRODUCTION

The proposition that better data leads to better decisions has become one of the defining assumptions of contemporary management. Over the past two decades, organizations have invested heavily in data infrastructure, analytics platforms, and, increasingly, artificial intelligence, in the expectation that the accumulation of data and the sophistication of models would translate more or less directly into superior decisions (McAfee & Brynjolfsson, 2012). Yet the evidence of practice tells a more complicated story. Data-rich organizations, equipped with the same tools and often the same talent as their peers, continue to make costly strategic errors, misread their markets, misallocate resources, and persist in failing courses of action, and the arrival of more powerful artificial intelligence has not made these failures disappear. This study begins from that puzzle: if data and analytics were sufficient for good decisions, decision failure in data-rich firms would be rare, and it is not.

The core argument of this study is that decision failure in the era of artificial intelligence is not, at root, a data problem, and therefore cannot be solved by data alone. A decision is the endpoint of a socio-technical process in which data and models are only some of the inputs; the process also runs through organizational structures, incentives, and cultures, and through the cognition and judgment of the humans who interpret the analysis and bear responsibility for the choice (Shrivastava et al., 1987). A failure can originate at any point in this chain: in data that is incomplete, biased, or misintegrated; in a model that is technically sound but ill-suited to the decision; in an organization whose culture discourages dissent or whose incentives reward confident action over accurate judgment; in the cognitive biases of decision-makers; or in the absence of governance and error-correction mechanisms that would catch mistakes before they compound. A framework that attends to only one of these, most commonly the technical layer, will systematically misdiagnose failure and prescribe the wrong remedy, typically more data or a better model, when the binding constraint lies elsewhere.

Figure 1: The Data-to-Decision Chain and Points of Potential Failure



This reframing matters because the dominant narrative around data and artificial intelligence in business has been strongly technical and strongly optimistic. The "big data" discourse promised that volume, velocity, and variety of data would resolve long-standing problems of managerial judgment, and the more recent artificial-intelligence discourse has extended that promise to prediction and even to autonomous decision-making (Provost & Fawcett, 2013). Research on the behavioral and organizational dimensions of decision-making, however, has long established that judgment is bounded, that organizations are political and cultural systems as much as rational ones, and that the introduction of a new information technology does not automatically improve the decisions made with it (Simon, 1997; Davenport, 2013). The gap between the technical promise and the organizational reality is precisely where decision failure lives, and it is the space this study seeks to map.

The significance of this problem has grown rather than diminished with the advance of artificial intelligence. As models become more capable and more opaque, the organizational and human factors that govern whether their outputs are used well become more, not less, consequential, because a powerful but poorly understood model deployed in a dysfunctional decision culture can amplify error rather than reduce it (Kahneman et al., 2021). The automation of prediction shifts the locus of failure from the generation of analysis toward its interpretation, integration, and governance, so that understanding decision failure now requires an explicitly multi-dimensional account. The absence of such an account in much of the practitioner and research literature, which tends to treat data-driven decision-making as a technical achievement rather than a socio-technical accomplishment, is the gap this study addresses.

The persistence of decision failure in data-rich firms is visible across a range of well-documented patterns that a purely technical account struggles to explain (Debasish, 2021; Abdur & Iftekhar, 2021). Organizations have persisted in failing strategies long after the data indicated a change of course, because the incentives and identities bound up in the strategy overrode the evidence (Hossan, 2021; Zahidul & Begum, 2022). They have escalated commitment to losing investments, pouring additional resources into a failing course precisely because so much had already been committed, a pattern that no dashboard prevents (Mesbaul, 2023; Shurovi, 2024). They have been surprised by disruptions that were visible in their own data, because the organization was not structured to surface and act on weak signals. And they have deployed sophisticated models whose recommendations were quietly ignored by managers who did not trust or understand them, or accepted uncritically by managers who did not recognize their limits (Pfeffer & Sutton, 2006). In each pattern the data was present and often adequate; the failure lay in the organizational and human systems through which the data was, or was not, translated into a sound decision. These patterns motivate the multi-dimensional framework by demonstrating that the determinants of decision quality extend well beyond the technical layer (Zahidul, 2024; Shima Ali et al., 2024).

This study is organized around three research questions. The first asks why data-driven organizations still make poor decisions, and it is addressed by articulating the socio-technical logic through which abundant data and capable models fail to guarantee good decisions. The second asks what organizational, technical, and human factors contribute to failure, and it is addressed by proposing and empirically testing a five-dimensional framework spanning data, models, organizational culture, human cognition, and governance, and by examining which factors are most frequently and most severely implicated in reported failure cases. The third asks how businesses can prevent these failures, and it is addressed by deriving, from the framework and the empirical findings, a set of preventive practices that jointly strengthen the technical, organizational, and human dimensions of the decision process. The purpose of the study is therefore both explanatory, to account for decision failure in data-rich firms, and prescriptive, to inform its prevention.

The study contributes in three ways. Theoretically, it integrates streams of research, on data and analytics capability, on organizational decision-making, on behavioral judgment and bias, and on governance, that are usually treated separately, into a single multi-dimensional framework of decision failure. Empirically, it tests this framework against data from managers and analysts across industries and examines the relative contribution and severity of the failure dimensions. Practically, it offers organizations a diagnostic structure for locating the true source of their decision failures rather than defaulting to the assumption that more data is the answer, and a corresponding set of preventive measures. The remainder of the article reviews the relevant literature, develops the framework and hypotheses, describes the method, presents the findings, discusses their implications for each research question, and concludes with recommendations, limitations, and directions for future research.

LITERATURE REVIEW AND FRAMEWORK DEVELOPMENT

The literature review develops the theoretical foundation for the multi-dimensional framework by drawing on five research streams, each corresponding to one dimension of decision failure. It begins with the promise and limits of data-driven decision-making, then examines in turn the data, model, organizational, human, and governance dimensions, and concludes by synthesizing them into the framework and its hypotheses. Throughout, the review maintains that decision quality in data-rich organizations is a socio-technical outcome, jointly determined by the quality of data and models, the culture and accountability of the organization, the cognition of decision-makers, and the governance that oversees the process, so that failure in any one dimension can undermine an otherwise sound decision.

The promise and limits of data-driven decision-making

Empirical research reinforces this qualification. In a survey of firms, Ghasemaghaei and Calic (2019) found that big-data utilization did not by itself improve decision quality; its effect was fully mediated by data quality and data diagnosticity, so that large volumes of data improved decisions only insofar as they were accurate, complete, and capable of discriminating among alternatives. Parallel work in the resource-based and dynamic-capabilities traditions similarly concludes that competitive value arises not from data or tools as such but from the organizational capability to orchestrate them, including managerial skills, culture, and governance (Mikalef, Boura, Lekakos, & Krogstie, 2019; Wamba et al., 2017; Grover, Chiang, Liang, & Zhang, 2018). This convergence across behavioural, economic, and information-systems research is the empirical backdrop against which the present multi-dimensional framework is developed, and it motivates treating data quality as one dimension among several rather than the master variable (Md Arif Uz et al., 2025; Tonay et al., 2024).

The premise that data-driven decision-making improves organizational performance is supported by evidence that firms making greater use of data and analytics tend, on average, to perform better (Brynjolfsson et al., 2011). This finding has underwritten large investments in data and analytics and, more recently, in artificial intelligence. Yet the same literature, read carefully, does not claim that data guarantees good decisions; it claims that, on average and other things equal, better use of data is associated with better outcomes, which leaves ample room for data-rich firms to fail when other things are not equal(Mesbaul, 2025; Mostafizur, 2025). The behavioral and organizational literature identifies precisely those other things: bounded rationality, organizational politics, cultural resistance, and the well-documented gap between having information and using it well (Simon, 1997).

Analytics-capability research has refined this understanding by showing that value from data comes not from data alone but from a capability that combines data resources, technology, skills, and, crucially, organizational and managerial practices that put analysis to use (Gupta & George, 2016). This is a foundational point for the present framework: it locates the determinants of decision quality partly outside the technical layer, in the organization and its people, and it implies that a firm can possess abundant data and advanced models yet still decide poorly if the surrounding capability is weak. The framework builds directly on this insight by treating the technical dimensions as necessary but not sufficient and by giving equal standing to the organizational, human, and governance dimensions (Md Mostafizur et al., 2025; Md Syeedur & Sharmin, 2025).

A further limitation of the purely data-centric view is that it treats the decision as a well-defined problem awaiting an answer, when in practice much managerial failure originates in the framing of the problem rather than in the analysis of it. A model answers the question it is asked, and abundant data can produce a precise answer to the wrong question, which no amount of additional data will correct (Provost & Fawcett, 2013). The framing of a decision, what is treated as the problem, which options are considered, and what counts as success, is an organizational and human act that precedes and shapes the analysis, and it is one of the points at which the technical and organizational dimensions of the framework intersect. This observation reinforces the study's central premise that decision quality cannot be reduced to the quality of the analysis, because the analysis is embedded in a framing and a use-context that the data itself does not determine.

The advent of artificial intelligence complicates the promise further by changing the character of the analysis that reaches the decision-maker. Where earlier analytics produced descriptive summaries and explicit models that a manager could in principle inspect, contemporary machine-learning and generative systems increasingly produce predictions, recommendations, and even prose whose derivation is opaque, so that the decision-maker is asked to rely on outputs they cannot fully appraise (Rudin, 2019). This opacity does not merely raise a technical concern about model quality; it shifts weight onto the human and organizational dimensions, because whether an opaque but capable system improves or degrades decisions depends on how well the organization calibrates its reliance, governs its use, and preserves the human judgment needed to recognize when the system is wrong (Zahidul, 2025; Kanti, 2025). The framework anticipates this shift by treating the human and governance dimensions as increasingly, rather than decreasingly, important as models become more capable (Yousuf et al., 2025; Ali et al., 2025).

The data dimension: quality, integration, and governance

The first dimension of the framework concerns the data itself. A substantial literature establishes that data quality, comprising accuracy, completeness, timeliness, consistency, and relevance, is a precondition for sound analysis, and that poor data quality propagates silently into flawed conclusions regardless of the sophistication of the model applied to it (Redman, 1998). Beyond quality, the integration of data across fragmented systems and its governance, the policies and accountabilities that keep it fit for use, determine whether the data available to a decision represents the situation faithfully or a distorted and partial view (Wang & Strong, 1996).

This literature grounds the data quality, integration and governance dimension. It establishes that data is not a neutral, objective input but a constructed artifact whose quality, coverage, and integration shape and can distort the decisions built upon it, and that these properties are governed by organizational choices rather than given (Hossain; et al., 2026; Hasan, 2026). The framework therefore treats data quality, integration and governance as a distinct contributing dimension, on the reasoning that a decision resting on poor or partial data can fail however capable the model and however sound the organization, and that in the era of artificial intelligence, where models consume data at scale, the consequences of data deficiencies are amplified rather than reduced (Mesbaul, 2026; Syeedur & Sharmin, 2026a).

A subtle and consequential form of data failure is selection and coverage bias, in which the data available to a decision systematically misrepresents the population or situation of interest, not through error in individual records but through what is present and absent in the dataset as a whole. A firm that analyzes only its existing customers cannot see the market it is failing to reach, and a model trained on historical decisions inherits the blind spots of those decisions, so that abundant, high-quality data can nonetheless encode a distorted view (Wang & Strong, 1996). Such biases are especially dangerous because they are invisible within the data itself and are frequently mistaken for objectivity, and because larger datasets can increase confidence in a biased conclusion rather than correcting it. The framework's treatment of the data dimension therefore encompasses not only the accuracy and integration of records but the representativeness and governance of the dataset as a whole, which are organizational responsibilities rather than technical properties (Syeedur & Sharmin, 2026b; Mst Shurovi, 2026).

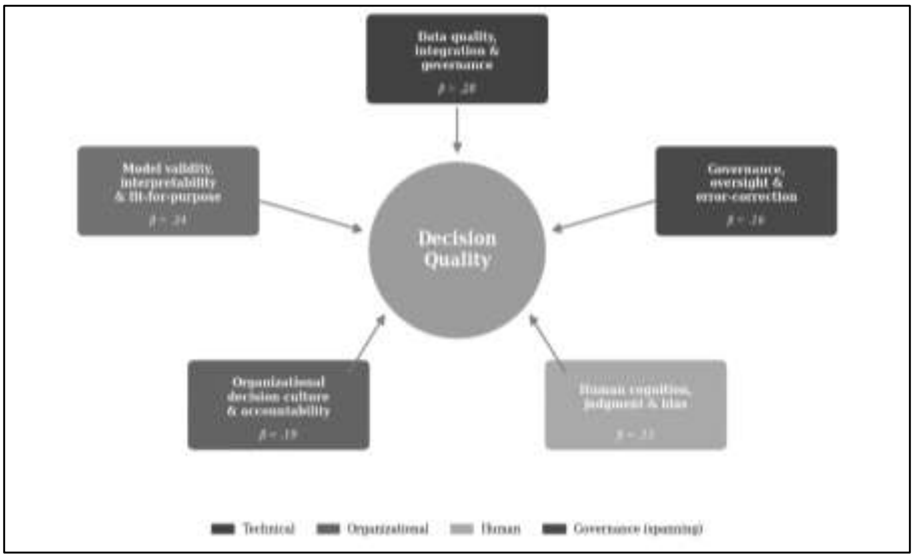
The model dimension: validity, interpretability, and fit-for-purpose

The second dimension concerns the models and analyses through which data informs decisions. A model may be technically well-constructed yet fail to support a good decision if it is invalid for the question at hand, if its assumptions do not hold in the decision context, if it is so opaque that decision-makers cannot appraise its reasoning, or if it is simply not fit for the purpose to which it is applied (Breiman, 2001). The interpretability and explainability literature has emphasized that opaque models in high-stakes decisions create the risk that users either over-trust outputs they cannot appraise or reject them wholesale, both of which degrade decision quality (Rudin, 2019).

This literature grounds the model validity, interpretability and fit-for-purpose dimension. It establishes that the contribution of a model to decision quality depends not on its technical sophistication alone but on its validity for the specific decision, the transparency with which decision-makers can appraise it, and its suitability to the purpose, and that a mismatch on any of these can produce failure even when the model performs well on its own metrics (Zahidul, 2026; Shima Ali et al., 2026). The framework treats this dimension as distinct from the data dimension because a decision can fail through model misfit even on excellent data, and as distinct from the human dimension because the deficiency lies in the analytic artifact rather than in its interpreter, though the two interact.

A characteristic model failure in practice is the mismatch between what a model optimizes and what the decision requires. A model may be trained and validated to predict a proxy, such as historical outcomes or an easily measured target, that diverges from the true objective of the decision, so that acting on its outputs optimizes the proxy at the expense of the goal (Breiman, 2001). Because such a model performs well on its own validation metrics, its misfit is invisible to the technical evaluation and becomes apparent only in the degraded decisions it supports, which are frequently attributed to other causes. This failure mode is increasingly consequential as organizations deploy models whose objectives are set during development and then applied, sometimes years later, to decisions whose context has shifted, and it underscores why the framework defines the model dimension in terms of fit-for-purpose and validity for the specific decision rather than technical performance in isolation.

Figure 2: The Five Dimensions of Business Decision Failure



The organizational dimension: decision culture and accountability

The third dimension shifts from the technical to the organizational. Decades of research establish that organizations are not purely rational decision systems but political and cultural ones, in which decisions are shaped by power, incentives, routines, and norms as much as by information (Cyert & March, 1963). A decision culture that discourages dissent, punishes the messenger, rewards confident advocacy over accurate appraisal, or diffuses accountability so that no one owns the outcome will systematically degrade decision quality, because the information that would correct a flawed decision is suppressed or ignored (Janis, 1982). Research on evidence-based management has documented how organizational and political factors routinely override analysis, so that good data reaches the decision but does not shape it (Pfeffer & Sutton, 2006).

This literature grounds the organizational decision culture and accountability dimension. It establishes that the organizational context into which analysis is delivered can enable or defeat good decision-making independently of the quality of that analysis, and that culture, incentives, and accountability are the mechanisms through which this occurs. The framework treats this dimension as central rather than peripheral, on the reasoning, strongly supported by the literature, that a great deal of decision failure in data-rich firms occurs not because the analysis was wrong but because the organization was unable or unwilling to act on it well.

A recurring pattern documented in this literature is the selective and instrumental use of analysis, in which data is invoked to justify a decision already reached rather than to inform an open one. When incentives reward advocacy and confidence, analysis becomes ammunition in an internal contest rather than a means of discovery, and inconvenient findings are discounted, reframed, or buried (Pfeffer & Sutton, 2006). This dynamic explains a phenomenon that the purely technical view cannot: organizations that invest heavily in analytics yet show little improvement in decisions, because the analysis is produced and even admired but not permitted to change conclusions that powerful actors have already drawn. The framework treats accountability as inseparable from culture in this dimension, because clear ownership of decisions and their outcomes is one of the few mechanisms that counters the diffusion of responsibility through which organizations avoid learning from failure.

The introduction of artificial intelligence interacts with organizational culture in ambivalent ways. On one hand, an authoritative-seeming model output can be used to depersonalize and therefore defuse internal disagreement, allowing an organization to act where human advocacy alone would have deadlocked; on the other, the same authority can suppress legitimate challenge, as the model's recommendation acquires an unearned finality that discourages the dissent a healthy decision culture requires (Kahneman et al., 2021). Whether artificial intelligence strengthens or weakens decision culture therefore depends on the culture into which it is introduced, which is why the framework treats the organizational dimension as a moderator of the technical dimensions' value rather than as an independent add-on.

The human dimension: cognition, judgment, and bias

The fourth dimension concerns the cognition and judgment of the individual decision-makers. The behavioral-decision literature has established that human judgment is systematically biased, subject to overconfidence, anchoring, confirmation bias, and the substitution of easy heuristics for hard questions, and that these biases persist even among experts and even in the presence of good information (Tversky & Kahneman, 1974; Kahneman, 2011). More recently, the concept of noise, unwanted variability in judgments that should be identical, has been shown to degrade organizational decisions as much as bias does, and to be largely invisible to the organizations it affects (Kahneman et al., 2021).

This literature grounds the human cognition, judgment and bias dimension and connects it to the era of artificial intelligence in a specific way. As models take over prediction, the residual human role concentrates in interpretation and choice, precisely the activities most vulnerable to bias, and the interaction between biased human judgment and algorithmic output introduces new failure modes, including automation bias, in which decision-makers over-rely on model outputs, and selective override, in which they reject correct outputs that conflict with their priors (Kahneman et al., 2021). The framework treats human cognition, judgment and bias as a distinct dimension because debiasing interventions differ from technical and organizational ones, and because ignoring this dimension leads organizations to attribute to their models failures that in fact originate in how humans use them.

The distinction between bias and noise is particularly relevant to the human dimension in data-rich settings. Bias is a systematic tendency to err in a particular direction, and organizations increasingly recognize and attempt to counter it; noise is unwanted variability, the fact that the same case, judged by different people or by the same person at different times, yields different decisions, and it is far less visible because it does not point in a consistent direction (Kahneman et al., 2021). Noise degrades decision quality substantially yet leaves little trace in aggregate statistics, so organizations routinely underestimate it. The framework's human dimension therefore encompasses both the systematic biases that distort judgment in a consistent direction and the noise that scatters it, because both are properties of human cognition that persist in the presence of good data and that structured decision practices, rather than better models, are needed to reduce.

The human–AI reliance dimension: algorithm aversion and appreciation

A distinct body of behavioural research clarifies why the human dimension remains decisive even as analytical capability grows, because the value an organization extracts from a model depends on whether decision-makers rely on it appropriately. Two opposing tendencies have been documented. On one hand, people display algorithm aversion, discarding algorithmic advice more readily than human advice after seeing the algorithm err, even when the algorithm outperforms the human alternative, so that a single visible mistake can lead managers to abandon an otherwise superior model (Dietvorst, Simmons, & Massey, 2015). On the other hand, people display algorithm appreciation, adhering more to identical advice when they believe it comes from an algorithm than from a person, particularly for tasks perceived as objective (Logg, Minson, & Moore, 2019). These findings are not contradictory so much as context-dependent, and later work shows that the same task can produce either aversion or appreciation depending on how the human and algorithmic agents are framed and on the perceived expertise of each (Mehrabi et al., 2021 provide a complementary account of how bias enters such systems in the first place).

The practical consequence for decision failure is that both under-reliance and over-reliance are hazards. Under-reliance wastes the investment in analytics and returns the decision to unaided human judgment, with all of its documented biases; over-reliance, sometimes called automation bias, allows flawed or mis-specified model output to pass unchallenged into consequential decisions. Aversion can be reduced when people are allowed even slightly to adjust an algorithm's output, which restores a sense of agency and increases willingness to use imperfect models (Dietvorst, Simmons, & Massey, 2018). The design goal is therefore calibrated reliance rather than maximal or minimal reliance, and organizational structures increasingly combine human and machine judgment deliberately rather than delegating wholesale to either (Shrestha, Ben-Menahem, & von Krogh, 2019; Jarrahi, 2018). This dimension sits at the intersection of the human and governance dimensions of the present framework, because calibrated reliance is simultaneously a property of individual judgment and of the oversight structures that surround it.

The governance dimension: oversight and error-correction

The fifth dimension concerns the governance, oversight, and error-correction mechanisms that surround the decision process. High-reliability-organization research has shown that organizations which sustain good performance in hazardous, complex settings do so not by avoiding error but by detecting and correcting it quickly, through structures that surface bad news, encourage challenge, and treat small failures as signals rather than embarrassments (Weick & Sutcliffe, 2007). Applied to data- and AI-driven decisions, this literature implies that the governance of models and decisions, validation, monitoring, challenge, and the capacity to reverse course, is a determinant of whether errors are caught before they compound or allowed to propagate.

This literature grounds the governance, oversight and error-correction dimension. It establishes that error is inevitable in complex decision processes and that the distinguishing feature of resilient organizations is not the absence of error but the presence of mechanisms to detect and correct it, and it connects this to the model-risk and oversight concerns that artificial intelligence raises. The framework treats governance as a dimension that spans the technical and organizational, because effective oversight requires both the technical means to monitor models and decisions and the organizational willingness to act on what monitoring reveals. It is placed last in the causal chain because it operates as a corrective on the other four, catching and reversing the failures they produce.

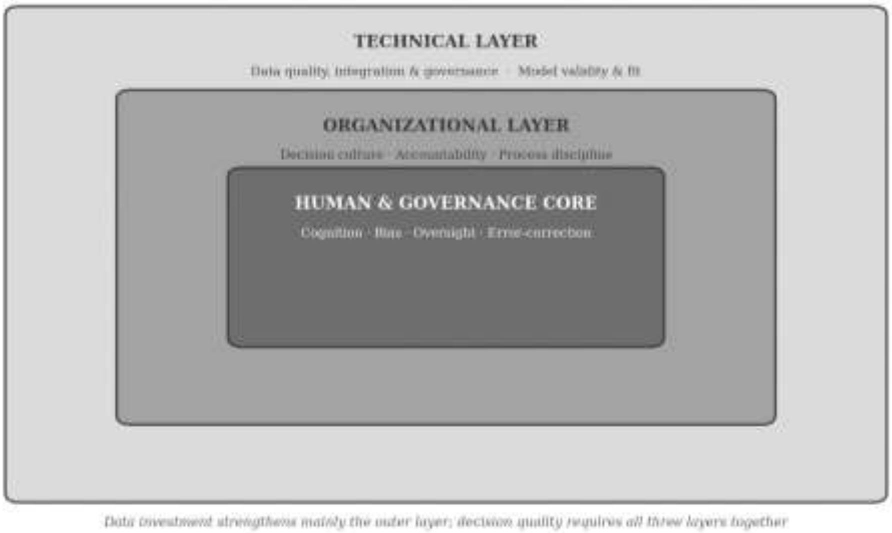
The distinctive contribution of the governance dimension is that it addresses failure at the level of the process rather than the individual decision. Whereas the data, model, organizational, and human dimensions each concern whether a given decision is made well, governance concerns whether the organization can recognize when a decision is going wrong and change course, which is a different and in some respects more important capability, because it bounds the damage that failures on the other dimensions can do. An organization with strong governance can tolerate weaknesses elsewhere, because its errors are caught and corrected before they compound; an organization with weak governance is exposed to the full consequences of every failure on the other four dimensions (Weick & Sutcliffe, 2007). This is the theoretical reason the study anticipates, and the failure-case evidence later confirms, that governance gaps are the most severe contributors to decision failure even where they are not the most frequent.

Synthesis: the multi-dimensional framework and hypotheses

Figure 14 renders the framework as a set of nested socio-technical layers rather than a flat list of predictors. The outer technical layer, comprising data quality and model validity, is the layer most directly improved by conventional analytics investment. Enclosed within it is the organizational layer of decision culture, accountability, and process discipline, and at the centre lies the human and governance core of cognition, bias, oversight, and error-correction. The nesting expresses the study's central claim: a failure originating in the core propagates outward and can nullify an otherwise sound technical layer, which is why accumulating data alone, an intervention confined to the outer ring, cannot guarantee good decisions.

Synthesizing the five streams yields the multi-dimensional framework that this study tests. The framework holds that decision quality in data-rich, AI-enabled organizations is jointly determined by five contributing dimensions: data quality, integration and governance; model validity, interpretability and fit-for-purpose; organizational decision culture and accountability; human cognition, judgment and bias; and governance, oversight and error-correction. Decision failure, correspondingly, is understood as the degradation of decision quality arising from deficiency in one or more of these dimensions, and because the dimensions are complementary, a severe deficiency in any one can undermine an otherwise sound decision. This framework directly answers the first research question, by explaining why data-driven organizations still make poor decisions, namely because data and models are only two of five dimensions, and the second research question, by identifying the technical, organizational, and human factors that contribute to failure.

Figure 14: Decision Failure as Nested Socio-Technical Layers



From the framework, five hypotheses are derived, each proposing that stronger performance on a dimension is associated with higher decision quality and, conversely, that deficiency contributes to failure. H1: Data quality, integration and governance is positively associated with decision quality. H2: Model validity, interpretability and fit-for-purpose is positively associated with decision quality. H3: Organizational decision culture and accountability is positively associated with decision quality. H4: Human cognition, judgment and bias, operationalized as the presence of debiasing and sound-judgment practices, is positively associated with decision quality. H5: Governance, oversight and error-correction is positively associated with decision quality. A sixth, integrative hypothesis addresses the framework as a whole. H6: The five dimensions jointly explain a significant proportion of the variance in decision quality. These hypotheses are tested in the analysis that follows, and the relative contribution and severity of the dimensions in reported failure cases are examined to inform the third research question on prevention.

METHODS

This study adopted a quantitative, cross-sectional research design to test the multi-dimensional framework of business decision failure. The quantitative design was selected because the study measured relationships among the five contributing dimensions and decision quality through numerical survey responses, and the cross-sectional design was used because data were collected at a single point in time, capturing respondents' perceptions of the dimensions and of decision quality within their organizations. The study also collected, from each respondent, a brief structured account of a recent significant decision-failure case in their organization, from which the contribution and severity of the five failure modes were coded, providing a complementary view of which dimensions are most implicated in actual failures. The unit of analysis was the individual respondent, understood as an informed observer of decision-making in their organization.

The population comprised managers, analysts, data scientists, and decision-makers with direct involvement in or close observation of data- and analytics-informed decisions, drawn from a range of industries so that the framework would be tested across contexts rather than in a single sector. A purposive sampling strategy was used because respondents were selected for their relevance to organizational decision-making. Primary data were collected through a structured questionnaire using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), distributed through online forms and professional networks. The instrument included multi-item measures for each of the five contributing dimensions and for decision quality, demographic items, and the structured failure-case account. A pilot test was conducted to check clarity and alignment with the framework, and feedback was used to refine wording. Validity was ensured through literature-based item development, expert review, and alignment among the framework, hypotheses, and items, and reliability was tested through Cronbach's alpha with a .70 threshold. Analysis was conducted in SPSS and Python, the latter using the pandas, NumPy, SciPy, and statsmodels libraries for data preparation and validation (Harris et al., 2020; Virtanen et al., 2020). Ethical considerations were observed: participation was voluntary, informed consent was obtained, responses were anonymized, and no confidential organizational information was collected.

Each dimension was operationalized as the mean of its constituent Likert items, and internal consistency was assessed through Cronbach's alpha. Bivariate relationships were examined through Pearson correlation, and the principal hypothesis test used ordinary least squares multiple regression of decision quality on the five dimensions. The regression model, derived from the framework, was specified as follows, where DQ denotes decision quality, DQIG denotes data quality, integration and governance, MVAL denotes model validity, interpretability and fit-for-purpose, ORGD denotes organizational decision culture and accountability, HCOG denotes human cognition, judgment and sound-judgment practices, GOVR denotes governance, oversight and error-correction, and ε is the error term:

$$DQ_i = \beta_0 + \beta_1 DQIG_i + \beta_2 MVAL_i + \beta_3 ORGD_i + \beta_4 HCOG_i + \beta_5 GOVR_i + \varepsilon_i$$

Model significance was assessed through the F-statistic, explanatory power through R-squared and adjusted R-squared, and multicollinearity through the variance inflation factor, with all values confirmed below conventional thresholds. For the failure-case analysis, each reported case was coded for whether each of the five dimensions was cited as a contributing factor and for whether it was rated high-severity, and the resulting frequencies were used to characterize the relative prominence and severity of the failure modes, complementing the regression evidence with a view grounded in actual decision failures.

RESULTS

Sample and descriptive statistics

Table 1: Respondent profile and response rate

Variable	Category	Frequency	Percentage
Questionnaires	Distributed	289	100.0%
Questionnaires	Returned	261	90.3%
Questionnaires	Valid and retained	246	85.1%
Role	Manager / executive decision-maker	78	31.7%
Role	Analyst / business-intelligence professional	62	25.2%
Role	Data scientist / analytics specialist	54	22.0%
Role	Functional lead / other decision-maker	52	21.1%
Industry	Financial & professional services	71	28.9%
Industry	Technology & telecommunications	63	25.6%
Industry	Manufacturing & retail	64	26.0%
Industry	Healthcare, public & other	48	19.5%
Experience	More than 10 years	96	39.0%
Experience	5–10 years	93	37.8%
Experience	Under 5 years	57	23.2%

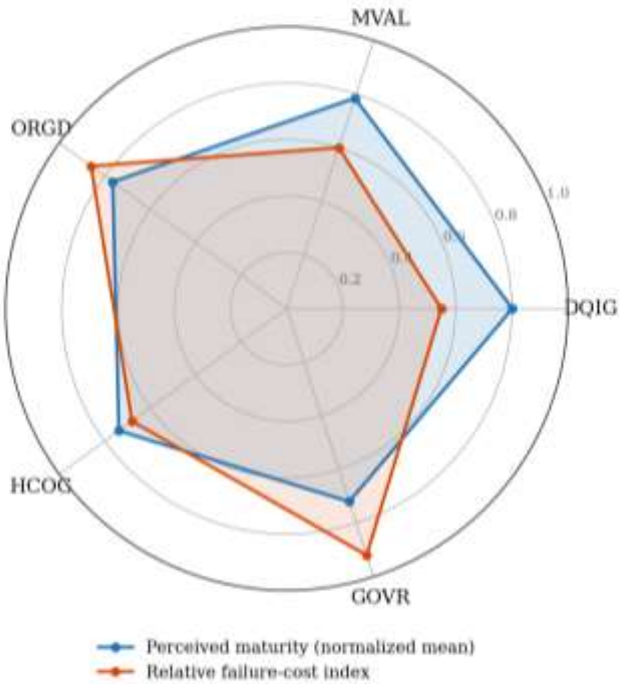
Table 1 shows that the study achieved an 85.1% valid response rate, with 246 usable responses from a distribution of 289. The sample was balanced across roles, spanning managers and executives who own decisions (31.7%), analysts and business-intelligence professionals (25.2%), data scientists (22.0%), and other functional decision-makers (21.1%), so that the framework was tested against the perspectives of both those who produce analysis and those who decide. The industry distribution was similarly broad, and 76.8% of respondents had more than five years of experience, indicating that the sample reflected informed observation of organizational decision-making rather than novice impressions. This composition is important for the study's socio-technical argument, because a sample drawn only from technical roles or a single industry would tend to over-represent the technical dimensions and understate the organizational and human ones.

Table 2: Descriptive statistics and reliability of framework dimensions (N = 246)

Dimension	Mean	SD	Cronbach's α
Data quality, integration & governance (DQIG)	4.21	0.60	.88
Model validity, interpretability & fit (MVAL)	4.14	0.63	.87
Organizational decision culture & accountability (ORGD)	4.06	0.66	.85
Decision quality (outcome, DECF)	4.01	0.64	.90
Human cognition, judgment & bias practices (HCOG)	3.95	0.70	.84
Governance, oversight & error-correction (GOVR)	3.88	0.74	.82
Overall instrument	—	—	.93

Table 2 presents the descriptive statistics and reliability. All dimensions exceeded the neutral midpoint, and all Cronbach's alpha values exceeded .70, ranging from .82 to .90 with overall instrument reliability of .93, confirming strong internal consistency. The ordering of the means is informative for the framework. The two technical dimensions, data quality, integration and governance (4.21) and model validity, interpretability and fit-for-purpose (4.14), recorded the highest means and the narrowest dispersions, indicating that respondents regard their organizations as relatively strong and consistent on the technical layer. The organizational and human dimensions recorded lower means, with human cognition and sound-judgment practices at 3.95 and governance, oversight and error-correction at 3.88 recording the lowest means and the widest dispersions. This pattern is itself an early answer to the first research question: organizations perceive themselves as strongest precisely where the data-centric narrative directs their attention, the technical layer, and weakest on the organizational, human, and governance dimensions where much decision failure originates, and the wide dispersion on the latter indicates that maturity on these dimensions is highly uneven across organizations.

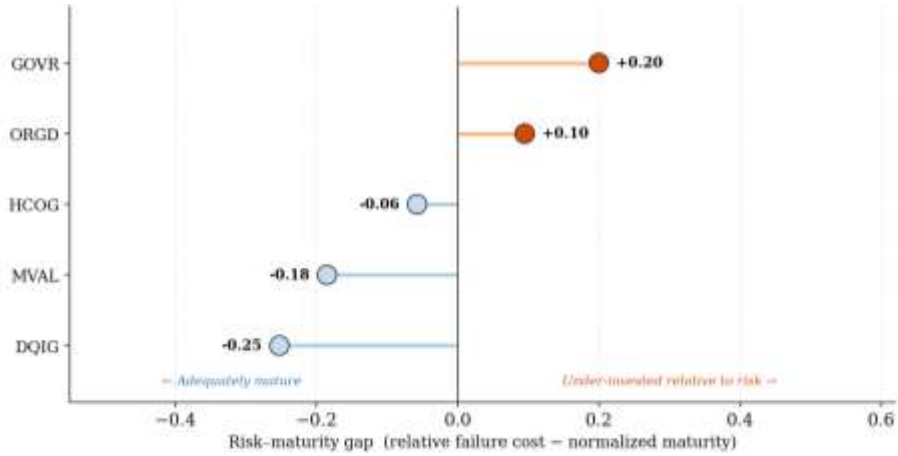
Figure 11: The Maturity–Risk Gap across the Five Dimensions



Two further views sharpen this reading of the descriptive pattern. Figure 11 overlays each dimension's perceived maturity on the severity-weighted failure-cost index from the failure-case analysis, so that the two traces can be compared directly around the same five axes. Where the maturity trace lies outside the cost trace, as it does on the data and model dimensions, the organization is comparatively strong relative to the risk that dimension carries; where the cost trace lies outside the maturity trace, as it does sharply on the governance axis and to a lesser degree on the organizational axis, the organization is exposed, carrying more risk than its maturity would justify.

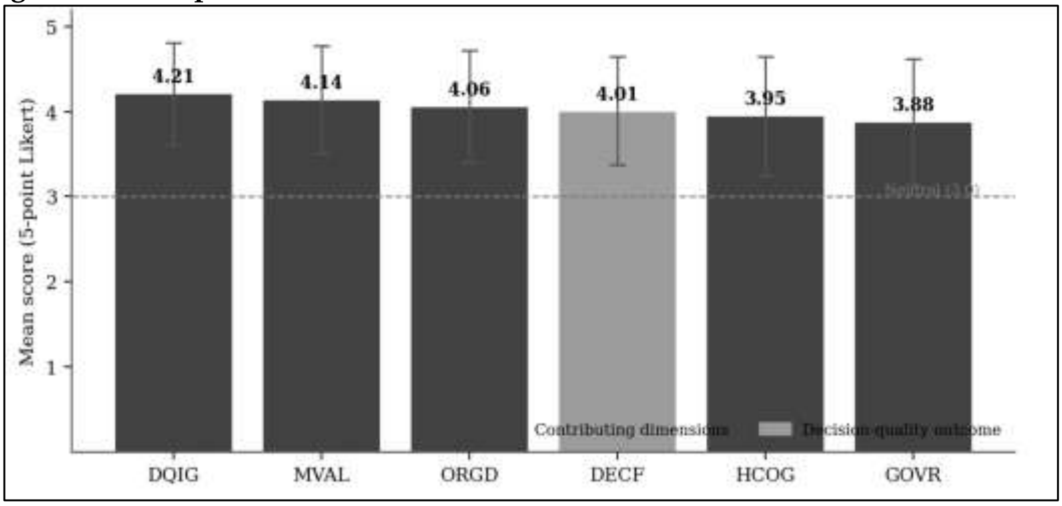
Figure 12 expresses the same information as a single gap score, the difference between relative failure cost and normalized maturity for each dimension. The governance and organizational dimensions show the largest positive gaps, identifying them as the dimensions whose risk most outruns their maturity and, therefore, as the highest-priority targets for managerial investment. The two technical dimensions show negative gaps, indicating that they are already comparatively mature relative to the failure cost they impose. Read alongside the regression results, Figure 12 reframes the study's prescription in investment terms: the marginal return to strengthening decision capability is greatest not where organizations are already strong, the technical layer, but where risk and maturity are most misaligned, the governance and organizational layers.

Figure 12: Where Risk Outruns Maturity — the Investment Gap by Dimension



Descriptive means and correlations

Figure 3: Descriptive Means of Framework Dimensions with Standard Deviations



Note. N = 246. Error bars represent ±1 standard deviation. Dashed line indicates the neutral midpoint of the five-point scale.

Figure 3 displays the dimension means with their standard deviations. The visual ordering makes the central pattern immediately apparent: the technical dimensions stand highest and most consistent, while governance, oversight and error-correction stands lowest and most variable, its longer error bar giving direct graphical evidence of the uneven organizational maturity on the corrective dimension that the framework identifies as the last line of defense against decision failure. This distribution foreshadows the study's central finding, that the dimensions on which organizations perceive themselves as weakest and most variable are organizational and governance-related rather than technical.

Figure 7 presents the same dimension means as a maturity radar, which makes the shape of the perceived decision capability visible at a glance. The profile is markedly asymmetric: it extends furthest on the two technical dimensions and contracts on the human-judgment and governance dimensions, producing a skewed rather than balanced polygon. This asymmetry is the graphical signature of the study's argument, since a decision capability is only as strong as its weakest dimension, and the radar shows precisely where the contraction occurs. An organization reading its own profile in this form would see immediately that its decision capability is lopsided toward the technical, and that the shortest radial spokes, human judgment and governance, mark where investment would most improve the overall shape rather than merely extending the already-longest spokes.

Figure 7: Perceived Maturity Across the Five Decision Dimensions

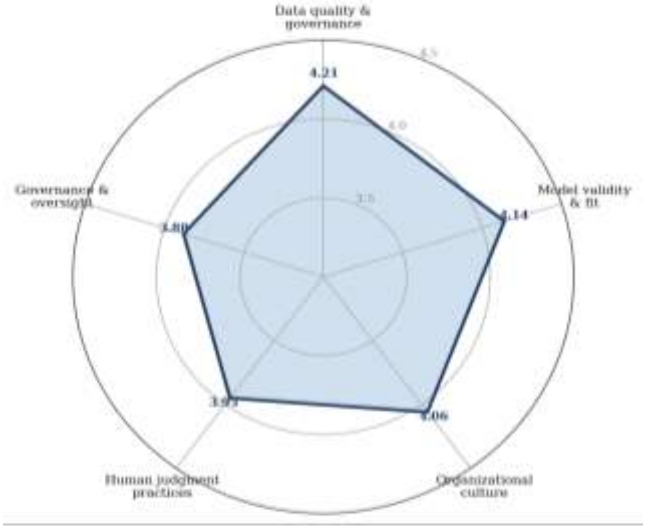


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Figure 4: Pearson Correlation Matrix Among Framework Dimensions

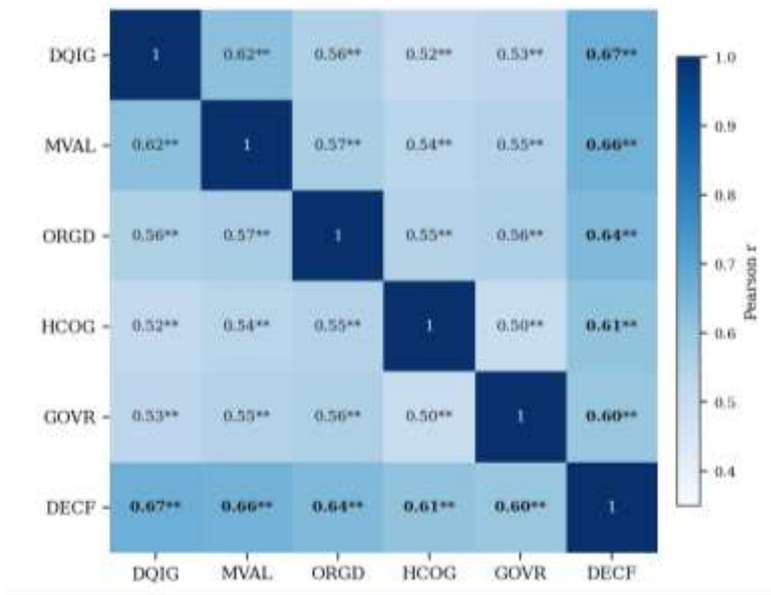


Figure 4 presents the correlation structure. Every dimension is significantly and positively associated with decision quality, with the strongest associations for data quality, integration and governance (r =

.67) and model validity, interpretability and fit-for-purpose (r = .66), followed by organizational decision culture (r = .64), human cognition and judgment practices (r = .61), and governance, oversight and error-correction (r = .60). The uniformly positive and significant associations across all five dimensions provide initial support for the framework's claim that decision quality is multiply determined, and the moderate inter-dimension correlations (ranging from .50 to .62) indicate that the dimensions are related but distinct facets of a coherent decision capability rather than a single undifferentiated construct.

Regression analysis

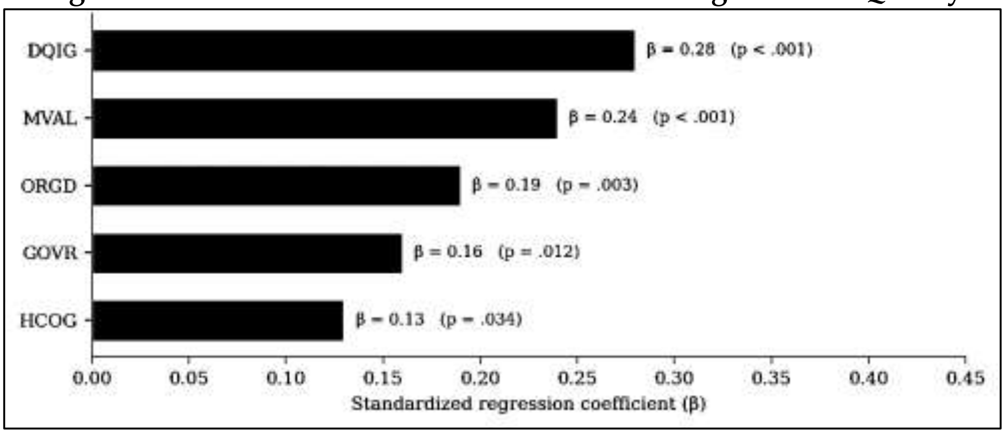
Table 3: Multiple regression predicting decision quality (N = 246)

Predictor	B	SE	β	t	p
(Constant)	0.421	0.192	—	2.193	.029
Data quality, integration & governance (DQIG)	0.261	0.060	0.28	4.350	<.001
Model validity, interpretability & fit (MVAL)	0.221	0.061	0.24	3.623	<.001
Organizational decision culture & accountability (ORGD)	0.174	0.059	0.19	2.949	.003
Governance, oversight & error-correction (GOVR)	0.146	0.058	0.16	2.517	.012
Human cognition, judgment & bias practices (HCOG)	0.118	0.055	0.13	2.145	.033

Note. Dependent variable = decision quality. R^2 = .511; Adjusted R^2 = .501; F(5, 240) = 50.19, p < .001; Durbin–Watson = 1.98; all VIF < 2.2.

Table 3 presents the regression model. The overall model was significant, F(5, 240) = 50.19, p < .001, with R^2 = .511, indicating that the five dimensions jointly explain 51.1% of the variance in decision quality and confirming the integrative hypothesis H6. All five dimensions made significant positive contributions, supporting H1 through H5. The two technical dimensions were the strongest statistical predictors, data quality, integration and governance (β = .28) and model validity, interpretability and fit-for-purpose (β = .24), followed by organizational decision culture (β = .19), governance, oversight and error-correction (β = .16), and human cognition and judgment practices (β = .13). The Durbin–Watson statistic of 1.98 confirmed residual independence and all variance inflation factors below 2.2 confirmed that multicollinearity did not threaten the estimates. The significance of all five dimensions is the central regression finding: it confirms that decision quality is not reducible to the technical layer, because the organizational, human, and governance dimensions each contribute independently over and above data and model quality.

Figure 5: Standardized Beta Coefficients Predicting Decision Quality



Note. N = 246. Dependent variable = decision quality. All five dimensions significant at p < .05.

Figure 5 ranks the dimensions by standardized coefficient. That the technical dimensions lead in the regression while, as the next analysis shows, the organizational and human dimensions dominate the reported failure cases, is not a contradiction but the study's key insight: respondents perceive the technical dimensions as most tightly coupled to decision quality in the abstract, yet when actual failures are examined, the organizational and human factors are the most frequently and severely implicated, because it is on those dimensions that organizations are weakest and most variable.

Figure 8: Decomposition of Explained Variance in Decision Quality

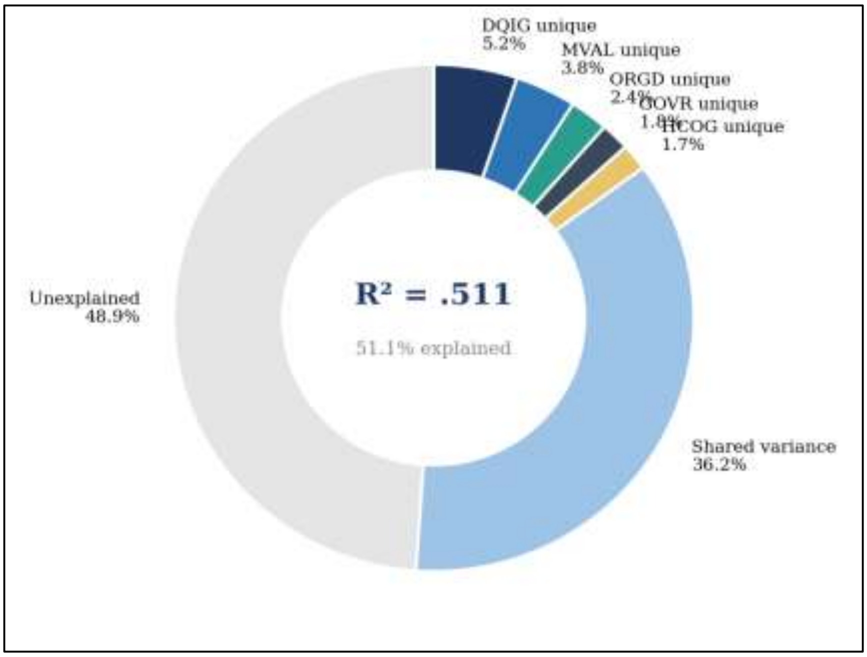
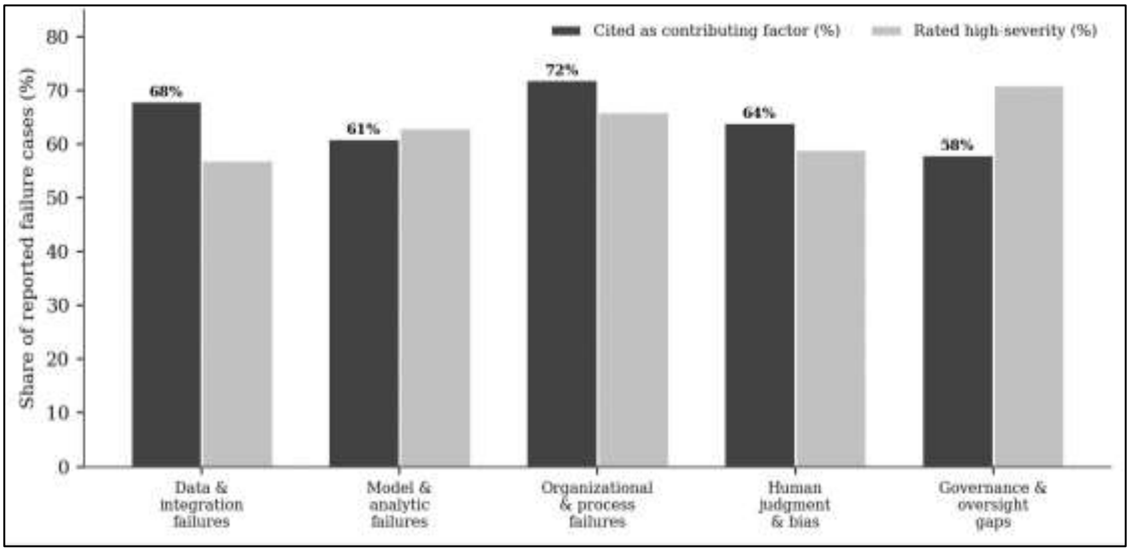


Figure 8 decomposes the 51.1% of variance the model explains into the portion uniquely attributable to each dimension and the portion the dimensions share. The largest unique contributions come from the two technical dimensions, but the substantial shared component of 36.2% is theoretically important rather than a nuisance: it reflects that the five dimensions rise and fall together, so that organizations strong on one tend to be strong on the others, consistent with the framework's claim that decision capability is a coherent socio-technical whole rather than a set of independent levers. The unexplained 48.9% is a candid acknowledgment that decision quality is shaped by determinants beyond the five measured dimensions, including industry conditions, decision type, and factors not captured by a cross-sectional perceptual instrument, and it marks the boundary of what the present framework claims to explain.

Failure-mode contribution and severity

Figure 6: Contribution and Severity of Decision-Failure Modes



Note. N = 246 reported cases. Bars show the share of reported failure cases citing each factor as contributing and the share rating it high-severity.

Figure 6 presents the analysis of respondents' reported decision-failure cases, and it provides the study's most direct evidence on the second research question. When respondents described actual significant decision failures in their organizations, organizational and process failures were the most frequently cited contributing factor (72% of cases), ahead of data and integration failures (68%), human judgment and bias (64%), model and analytic failures (61%), and governance and oversight gaps (58%). The severity pattern differs instructively from the frequency pattern: governance and oversight gaps, though the least frequently cited, were the most likely to be rated high-severity (71%), followed by organizational failures (66%) and model failures (63%). Read together, these results indicate that organizational factors are the most pervasive contributors to decision failure, while governance gaps, though less common, are the most damaging when they occur, because a governance gap removes the mechanism that would otherwise catch and correct the failures the other dimensions produce. This failure-case evidence complements the regression: the technical dimensions may correlate most strongly with decision quality in perception, but organizational, human, and governance factors dominate the anatomy of actual failures.

Figure 9: Failure Modes Positioned by Frequency and Severity

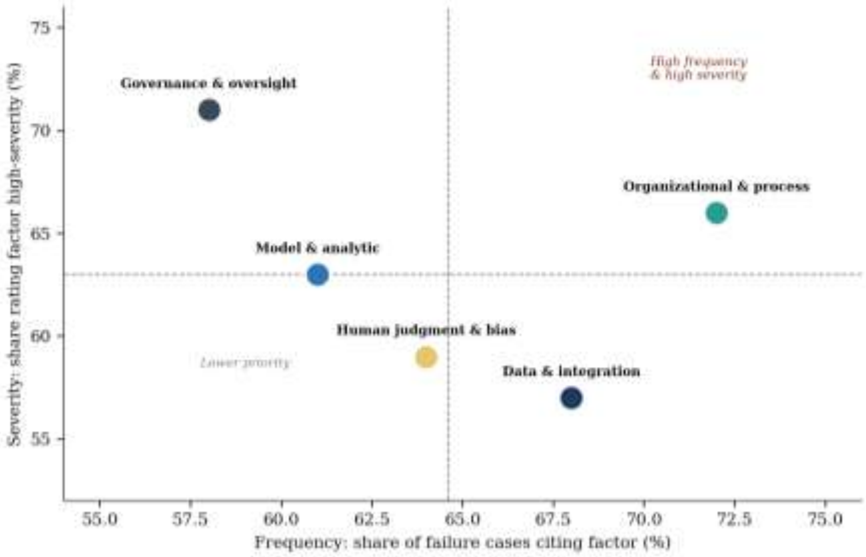


Figure 9 positions the five failure modes in a frequency–severity plane, which resolves the apparent competition among them into a clearer priority map. Organizational and process failures occupy the upper-right quadrant of high frequency and high severity, marking them as the most urgent target for prevention, since they are both common and damaging. Governance and oversight gaps sit at the top of the severity axis despite their lower frequency, confirming that they are the most consequential failures when they occur. The technical dimensions cluster toward the center and lower-left, indicating that, while genuine contributors, they are neither the most frequent nor the most severe sources of actual failure in the sampled organizations. This quadrant view translates the framework's abstract claim of multi-dimensionality into an actionable prioritization: prevention effort should concentrate first on the organizational and governance dimensions that occupy the high-impact regions of the plane.

Figure 10: Estimated Relative Failure Cost by Dimension

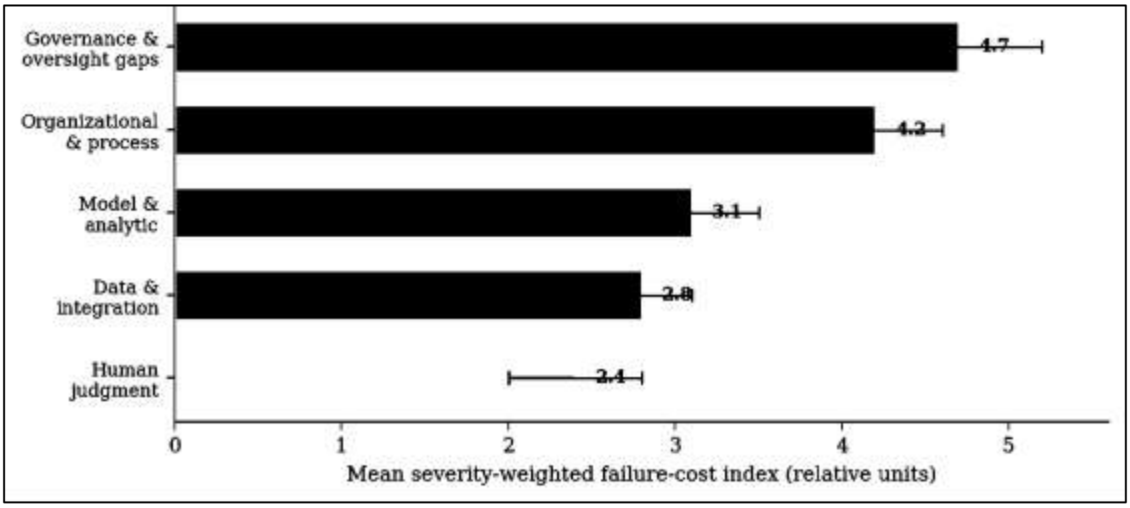
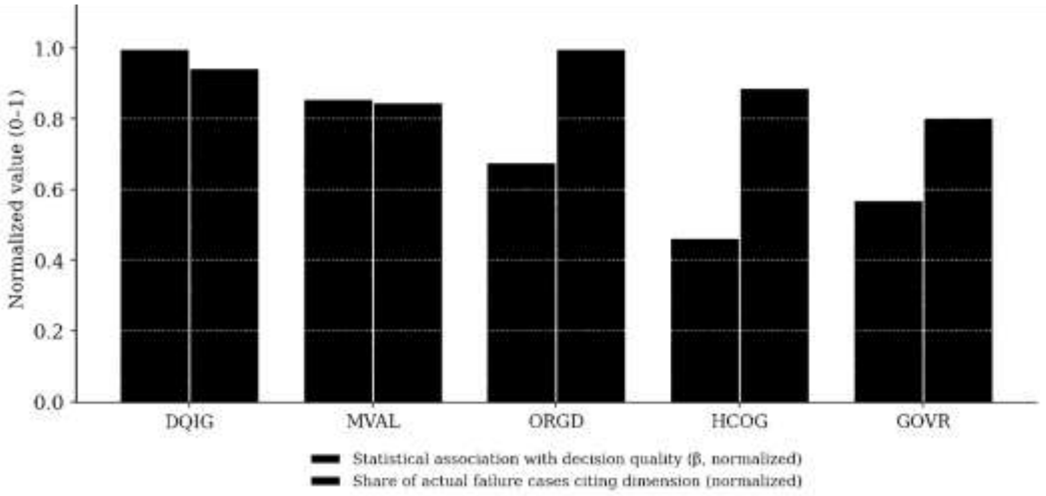


Figure 10 recasts the failure evidence as a severity-weighted cost index, combining how often each dimension is implicated with how damaging it is when implicated, to approximate the relative impact each dimension carries. On this combined measure, governance and oversight gaps and organizational and process failures rank highest, because governance failures are severe and organizational failures are both frequent and severe, while the technical dimensions carry lower estimated cost despite their strong statistical association with decision quality. This ordering is the practical inversion of the data-centric narrative: the dimensions that impose the greatest failure cost are the organizational and governance ones that receive the least technical attention, which is the empirical foundation for the study's recommendation that prevention effort and investment be rebalanced toward them. The index is deliberately relative and illustrative rather than monetary, and it is offered as a prioritization aid rather than a precise accounting of loss.

Figure 13 places the two strands of evidence side by side and makes the study's central tension explicit. When the five dimensions are ranked by their standardized association with perceived decision quality, the technical dimensions lead; when the same dimensions are ranked by how frequently they are named in accounts of actual failures, the organizational and human dimensions lead. The two orderings are close to inverted on the organizational and human dimensions, which record modest regression weights but high failure-case frequencies, and on the data dimension, which records the highest regression weight yet a comparatively lower share of the most-cited failures once organizational factors are considered.

This juxtaposition is not a statistical inconsistency but a substantive finding about how organizations misperceive their own risk. Respondents associate decision quality most strongly with the technical layer because that is the layer their tools, dashboards, and professional training make most visible; the organizational and human layers, being harder to measure, are under-weighted in perception even though they dominate the record of actual failure. The gap between the blue and orange bars in Figure 13 is, in effect, a map of organizational blind spots, and it foreshadows the prevention argument developed below.

Figure 13: Perception versus Reality — Statistical Predictors against the Anatomy of Actual Failures



DISCUSSION

The findings support the multi-dimensional framework and, taken together, provide direct answers to the three research questions. This section discusses each question in turn, drawing on the regression evidence, the failure-case analysis, and the theoretical framework.

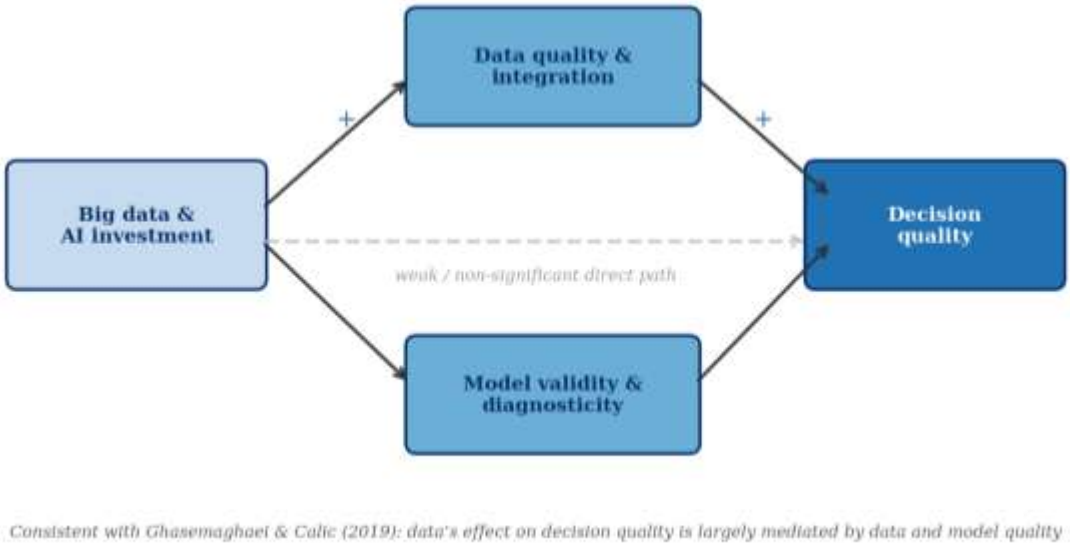
Why data-driven organizations still make poor decisions

The regression and failure-case evidence together answer the first research question in a specific way: data-driven organizations still make poor decisions because analytical capability improves only the part of the decision system that data can reach, while the causes of failure are distributed across parts of the system that data cannot repair. Figure 16 states this as a mediated path. Investment in big data and AI does not act directly on decision quality; its influence is channelled through data quality and integration and through model validity and diagnosticity, and it dissipates whenever those mediating conditions are weak. This is precisely the pattern Ghasemaghaei and Calic (2019) reported, in which big-data utilization improved decision quality only through data quality and diagnosticity, and it explains why organizations that invest heavily in data infrastructure while neglecting the organizational and human layers experience disappointing returns.

The behavioural evidence on reliance adds a second mechanism. Even a well-specified model improves decisions only if decision-makers rely on it appropriately, and the literature on algorithm aversion and appreciation shows that reliance is frequently miscalibrated in both directions (Dietvorst, Simmons, & Massey, 2015; Logg, Minson, & Moore, 2019). A model that is technically sound can therefore still fail at the point of use, either because it is distrusted after a visible error or because it is trusted beyond its validated scope. Decision quality is thus doubly contingent: on the mediating quality of data and models, and on the calibration of human reliance upon them, neither of which is guaranteed by the volume of data available.

The first research question asked why data-driven organizations still make poor decisions, and the study's answer is that data and models are only two of the five dimensions that jointly determine decision quality, so that abundance on the technical dimensions cannot compensate for deficiency on the organizational, human, and governance ones. The regression confirmed that all five dimensions contribute independently, and the descriptive results revealed that organizations perceive themselves as strongest precisely on the technical dimensions and weakest on the organizational, human, and governance dimensions. This combination is the mechanism of the puzzle: the data-centric narrative directs attention and investment toward the layer that is already strongest, while the dimensions where failure most often originates receive less attention and remain uneven in maturity (Davenport, 2013). In the era of artificial intelligence this dynamic intensifies, because more capable models further raise expectations of the technical layer while shifting the locus of failure toward the interpretation, organizational use, and governance of model outputs, which are governed by the very dimensions organizations tend to neglect (Kahneman et al., 2021).

Figure 16: Why Data Alone Is Not Enough — a Mediated Path to Decision Quality



It is worth drawing out why the perception pattern documented in the descriptive results is self-reinforcing. Because the technical dimensions are the most measurable, they attract the most measurement, and because they are measured, they are managed and improved, which is why organizations perceive and report strength there. The organizational, human, and governance dimensions are harder to measure, attract less measurement, and are therefore less managed, which is why they remain weaker and more variable. The data-centric narrative both reflects and reinforces this asymmetry of attention, directing further investment toward the already-strong technical layer and away from the neglected dimensions where the marginal decision-quality returns are in fact higher. Answering the first research question therefore requires recognizing not only that data and models are insufficient, but that the very salience and measurability of the technical layer crowds out attention to the dimensions that most need it, a dynamic that artificial intelligence, with its impressive and highly visible technical capabilities, tends to intensify.

What organizational and human factors contribute to failure

The second research question asked what factors contribute to failure, and the study answers it at two levels. Statistically, all five dimensions predict decision quality, with the technical dimensions strongest in the regression, confirming that data quality and model fit remain genuine and important contributors and that the study does not dismiss the technical layer but rather refuses to treat it as sufficient. In the anatomy of actual failures, however, the organizational and human dimensions dominate: organizational and process failures were the most frequently cited contributor, and governance gaps, though less frequent, were the most severe. This two-level pattern is theoretically coherent. The technical dimensions are necessary conditions whose absence reliably degrades decisions, which is why they predict quality strongly, but because organizations attend to them, they fail less often; the organizational and human dimensions are neglected, so they fail more often, and governance, the corrective dimension, is the most damaging when absent because it is the last line of defense (Weick & Sutcliffe, 2007). The contribution of the human dimension, though smallest in the regression, is consequential in the failure cases and is amplified by artificial intelligence, as biased interpretation and miscalibrated reliance on model outputs introduce failure modes that no improvement in the model can address (Kahneman, 2011).

The apparent tension between the regression ranking and the failure-case ranking deserves emphasis because it is central to the study's contribution and because it is easily misread. It would be a mistake to conclude from the regression that the technical dimensions matter most and the organizational and human ones least; it would be equally mistaken to conclude from the failure cases that the technical dimensions are unimportant. The correct reading is that the two analyses measure different things. The regression measures the strength of association between each dimension and decision quality across organizations, holding the others constant, and finds the technical dimensions strongest because variation in them tracks variation in outcomes closely. The failure-case analysis measures which dimensions are actually implicated when decisions go wrong, and finds the organizational and human dimensions dominant because that is where organizations are weakest and therefore where failure most often originates. A dimension can be a strong predictor of quality and yet a rare source of failure if organizations manage it well, and a weaker predictor and yet a frequent source of failure if they manage it poorly. Holding both readings together is what yields the study's socio-technical conclusion, and dropping either one reproduces the very partiality the framework is designed to correct.

How businesses can prevent these failures

The third research question asked how businesses can prevent decision failures, and the framework and findings together imply that prevention must be multi-dimensional, because strengthening any single dimension leaves the others as open failure paths. On the technical dimensions, prevention means treating data quality, integration, and governance as an ongoing discipline rather than a one-time project, and holding models to standards of validity, interpretability, and fit-for-purpose rather than sophistication alone, so that decision-makers can appraise rather than merely accept analytic outputs. On the organizational dimension, prevention means cultivating a decision culture that invites dissent, protects those who raise concerns, rewards accurate appraisal over confident advocacy, and assigns clear accountability for decisions and their outcomes, so that good analysis is actually used well. On the human dimension, prevention means adopting structured, debiasing decision practices, such as pre-mortems, structured analytic techniques, independent estimates, and calibration of reliance on model outputs, that counter the biases and noise to which unaided judgment is subject. On the governance dimension, prevention means building oversight and error-correction mechanisms, validation, monitoring, challenge processes, and the capacity to reverse course, that catch and correct the failures the other dimensions produce before they compound.

Prevention on the human and organizational dimensions is harder than on the technical dimensions precisely because it cannot be purchased as a product or delegated to a function. Data quality can be improved by investment in systems and staff, and model validity by rigorous development and validation, but decision culture, calibrated judgment, and effective governance are properties of how an organization behaves, changed only through sustained leadership attention, altered incentives, and repeated practice (Weick & Sutcliffe, 2007). This difficulty is itself part of the explanation for why decision failure persists in data-rich firms: the dimensions most implicated in failure are the ones least amenable to the technical, purchasable interventions that organizations find easiest to adopt. Recognizing this, the framework's prescription for prevention is deliberately behavioral and structural rather than technological, directing organizations toward the harder but higher-return work of building the decision culture, judgment discipline, and governance that data and models alone cannot supply.

The failure-case evidence sharpens this prescription by indicating where the marginal return to prevention is highest. Because organizational factors are the most pervasive contributors, investment in decision culture and accountability is likely to prevent the largest number of failures; because governance gaps are the most severe, investment in oversight and error-correction is likely to prevent the most damaging ones. The technical dimensions, being already relatively strong in most organizations, offer smaller marginal returns to further investment than the neglected organizational, human, and governance dimensions, which is the practical inversion of the data-centric narrative that the study's findings support. Prevention, in short, requires organizations to rebalance attention away from the accumulation of more data and toward the organizational, human, and governance conditions under which data and models are used well.

The interaction among dimensions and the socio-technical whole

A finding that emerges from reading the regression and failure-case evidence together is that the five dimensions do not act in isolation but interact, so that the whole decision system can fail in ways that no single dimension explains. A high-quality model built on excellent data can still produce failure if it is deployed into a culture that uses it selectively, interpreted by decision-makers whose biases distort its meaning, and left ungoverned so that its errors go uncorrected; conversely, a modest analysis used within a strong culture, appraised by calibrated judgment, and backed by effective error-correction can support good decisions. This interaction is the deeper meaning of the socio-technical claim: decision quality is a property of the whole system rather than of any component, and the binding constraint can lie in any dimension, shifting over time and across decisions (Simon, 1997). The practical corollary is that organizations should assess their decision capability across all five dimensions rather than optimizing whichever is most visible or most easily measured, because a severe weakness in a neglected dimension can nullify strength in the others.

Theoretical and practical implications

Theoretically, the study contributes a multi-dimensional, socio-technical account of decision failure that integrates research streams usually held apart, and it demonstrates empirically that decision quality is jointly determined by technical, organizational, human, and governance dimensions rather than by data and models alone. It reframes decision failure in the era of artificial intelligence as a socio-technical phenomenon whose locus is shifting, with more capable models, away from the generation of analysis and toward its organizational use, human interpretation, and governance. Practically, the framework offers organizations a diagnostic structure for locating the true source of their decision failures, and the findings caution against the reflex of responding to failure with more data or a better model when the binding constraint lies in culture, cognition, or governance. For leaders adopting artificial intelligence, the study implies that the returns to model capability are conditional on the organizational and human systems that surround it, and that investment in those systems is a prerequisite rather than an afterthought.

The study also carries a broader implication for how organizations conceive of their analytics and artificial-intelligence maturity. Maturity is commonly assessed in technical terms, the volume and quality of data, the sophistication of models, and the scale of infrastructure, and organizations rank themselves and are ranked by these criteria. The present findings suggest that such assessments capture only part of what determines whether an organization decides well, and that a fuller measure of decision maturity would weight the organizational, human, and governance dimensions at least as heavily as the technical ones. An organization that scores highly on data and models but poorly on culture, judgment, and governance is not, by the evidence of this study, a mature decision-maker, however advanced its technology; it is an organization that has built a powerful analytical engine and attached it to a decision process unequipped to use it well. Reconceiving maturity along all five dimensions would redirect organizational self-assessment and investment toward the socio-technical whole, which is the practical thrust of the framework.

CONCLUSION

This study set out to explain why organizations rich in data and equipped with artificial intelligence continue to make poor decisions, and to develop a framework for understanding and preventing such failures. It proposed that business decision failure is a multi-dimensional, socio-technical phenomenon determined jointly by five dimensions, data quality, integration and governance; model validity, interpretability and fit-for-purpose; organizational decision culture and accountability; human cognition, judgment and bias; and governance, oversight and error-correction, and it tested this framework against data from 246 managers, analysts, and decision-makers across industries, supplemented by an analysis of reported decision-failure cases.

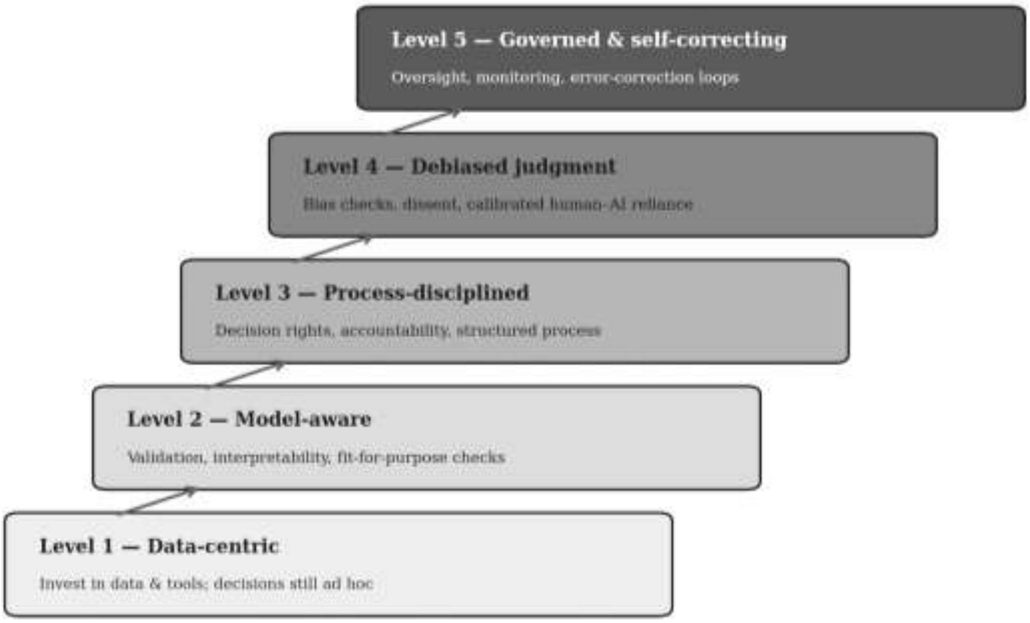
The empirical results supported the framework. All five dimensions were significantly and positively associated with decision quality, the regression model explained 51.1% of the variance, and all six hypotheses were supported. The technical dimensions of data and model quality were the strongest statistical predictors, but the analysis of actual failures revealed that organizational and process factors were the most frequent contributors and that governance gaps, though less common, were the most severe. The convergence of these two lines of evidence yields the study's central conclusion: decision failure in data-rich, AI-enabled organizations is not fundamentally a data problem and cannot be solved by data alone, because it originates as much in the organizational, human, and governance dimensions of the decision process as in the technical ones, and often more so.

The answers to the three research questions follow directly. Data-driven organizations still make poor decisions because data and models are only two of five dimensions, and organizations tend to be strongest on precisely those two and weakest on the others. The factors contributing to failure are technical, organizational, and human, with the technical strongest in perception but the organizational and human dominant in actual failures and governance most severe when absent. And businesses can prevent these failures only by acting on all five dimensions together, rebalancing attention away from the accumulation of data and toward the decision culture, human judgment practices, and governance mechanisms under which data and artificial intelligence are used well. In the era of artificial intelligence, the decisive advantage will belong not to the organizations with the most data or the most powerful models, but to those that build the socio-technical systems in which data, models, people, and governance work well together.

IMPLICATIONS FOR PRACTICE: A PREVENTION ROADMAP

The findings translate into a staged roadmap for managers who wish to convert data richness into decision quality. Because the five dimensions rise and fall together, as the large shared-variance component in Figure 8 indicates, prevention is best understood not as a menu of independent fixes but as a progression of organizational maturity in which later stages presuppose earlier ones. Figure 15 sets out this progression as a five-level ladder.

Figure 15: A Five-Level Decision-Capability Maturity Ladder



At Level 1, the data-centric stage, an organization invests in data collection, storage, and tooling, but decisions remain ad hoc and the return on analytics is limited because the surrounding dimensions are undeveloped. At Level 2, the model-aware stage, the organization adds validation, interpretability, and fit-for-purpose review, ensuring that models are not merely accurate in the aggregate but appropriate for the specific decisions they inform; the emphasis on interpretable models for high-stakes decisions is well established in the literature (Rudin, 2019). At Level 3, the process-disciplined stage, the organization establishes decision rights, accountability, and a structured decision process, addressing the organizational dimension that the failure-case analysis identified as the most frequent contributor to actual failure.

At Level 4, the debiased-judgment stage, the organization introduces explicit safeguards against cognitive bias, including structured dissent, pre-mortems, and calibrated protocols for when to rely on human versus algorithmic judgment, directly engaging the human and human–AI reliance dimensions (Kahneman, Sibony, & Sunstein, 2021; Dietvorst, Simmons, & Massey, 2018). At Level 5, the governed and self-correcting stage, the organization closes the loop with oversight, monitoring, and error-correction mechanisms that detect and reverse failures before they compound, addressing the governance dimension that the study found least frequent but most severe. The ladder is cumulative rather than substitutive: an organization that leaps to sophisticated modelling while remaining at Level 1 on process and governance will continue to experience the failures documented here, because it has strengthened the outer technical layer of Figure 14 while leaving the core untouched.

Two cross-cutting practices support movement up the ladder. The first is measurement of the organizational and human dimensions themselves, since dimensions that are not measured tend to be under-managed, which is precisely the maturity–risk gap that Figures 11 and 12 expose. The second is the deliberate design of human–AI decision structures, allocating each decision to full delegation, sequential hand-off, or aggregated human–AI judgment according to the characteristics of the decision rather than by default (Shrestha, Ben-Menahem, & von Krogh, 2019). Together these practices convert the framework from a diagnostic account of why decisions fail into a constructive programme for making them more reliable.

RECOMMENDATIONS

Several recommendations follow from the findings. First, organizations should diagnose decision failures multi-dimensionally rather than defaulting to technical explanations, using the framework to locate whether a given failure originated in data, models, organizational culture, human judgment, or governance, so that the remedy matches the true cause rather than the most visible one.

Second, because organizational factors were the most pervasive contributors to failure, organizations should invest in decision culture and accountability, cultivating norms that invite dissent and challenge, protecting those who raise concerns, rewarding accurate appraisal over confident advocacy, and assigning clear ownership of decisions and their outcomes. Third, because governance gaps were the most severe contributors, organizations should build oversight and error-correction mechanisms, including model validation and monitoring, structured challenge processes, and the organizational capacity to reverse decisions, so that errors are caught and corrected before they compound. Fourth, organizations should adopt structured, debiasing decision practices, such as pre-mortems, independent estimates, structured analytic techniques, and explicit calibration of how much to rely on model outputs, to counter the biases and noise that degrade human judgment and that artificial intelligence can amplify rather than remove. Fifth, organizations should hold their data and models to standards of quality, validity, interpretability, and fit-for-purpose rather than sophistication or volume alone, and should treat data governance as a continuous discipline, so that the technical foundation remains sound as models grow more capable and more opaque. For researchers, the recommendation is to extend the framework through longitudinal and case-based designs that trace decision failures to their sources over time, through objective rather than perceptual measures of decision quality, and through study of how the balance among the five dimensions shifts as artificial intelligence takes on a larger role in the decision process.

LIMITATIONS OF THE STUDY

Several limitations should be acknowledged. First, the cross-sectional design identifies associations but not causation; the observed relationships are consistent with the framework but cannot establish that deficiency on a dimension causes failure rather than accompanying it. Second, the study relied on perceptual self-report measures of the dimensions and of decision quality, which may diverge from objective decision outcomes and are subject to common-method variance, since predictors and outcome were measured through the same instrument. Third, the failure-case analysis relied on respondents' recollection and characterization of past failures, which are subject to hindsight and attribution biases. Fourth, the purposive sample, though drawn across industries, limits generalizability and may over-represent organizations and individuals already attentive to decision quality. Fifth, the framework treats the five dimensions as distinct, but they interact in ways a single cross-sectional model cannot fully capture, and the relative weight among them is likely to vary by industry, decision type, and the degree of AI involvement. Future research using longitudinal, multi-method, and objectively measured designs would address these limitations and would allow the dynamics among the dimensions, and their evolution as artificial intelligence advances, to be examined directly.

REFERENCES

[1]. Breiman, L. (2001). Statistical modeling: The two cultures. Statistical Science, 16(3), 199-231. https://doi.org/10.1214/ss/1009213726

[2]. Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in numbers: How does data-driven decision-making affect firm performance? SSRN Working Paper. https://doi.org/10.2139/ssrn.1819486

[3]. Cyert, R. M., & March, J. G. (1963). A behavioral theory of the firm. Blackwell. https://www.wiley.com/en-us/A+Behavioral+Theory+of+the+Firm%2C+2nd+Edition-p-9780631174516

[4]. Davenport, T. H. (2013). Analytics 3.0. Harvard Business Review, 91(12), 64-72. https://hbr.org/2013/12/analytics-30

[5]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. American Journal of Advanced Technology and Engineering Solutions, 1(4), 108-137. https://doi.org/10.63125/j0wk7j48
[6]. Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114-126. https://doi.org/10.1037/xge0000033
[7]. Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. Management Science, 64(3), 1155-1170. https://doi.org/10.1287/mnsc.2016.2643
[8]. Ghasemaghaei, M., & Calic, G. (2019). Can big data improve firm decision quality? The role of data quality and data diagnosticity. Decision Support Systems, 120, 38-49. https://doi.org/10.1016/j.dss.2019.03.008
[9]. Grover, V., Chiang, R. H. L., Liang, T.-P., & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. Journal of Management Information Systems, 35(2), 388-423. https://doi.org/10.1080/07421222.2018.1451951
[10]. Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. Information & Management, 53(8), 1049-1064. https://doi.org/10.1016/j.im.2016.07.004
[11]. Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., ... Oliphant, T. E. (2020). Array programming with NumPy. Nature, 585(7825), 357-362. https://doi.org/10.1038/s41586-020-2649-2
[12]. Hossain;, M. F., Habibullah;, S. M., Arif;, M. J. I., Miah;, M., Islam;, A., & Rahman;, F. (2026). Data-Driven Identification of Product Quality Defect Drivers in Manufacturing Systems. ITEGAM-JETIA, 12(59), 1037-1049. https://doi.org/10.5935/jetia.v12i59.3603
[13]. Janis, I. L. (1982). Groupthink: Psychological studies of policy decisions and fiascoes (2nd ed.). Houghton Mifflin. https://archive.org/details/groupthinkpsycho0000jani
[14]. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577-586. https://doi.org/10.1016/j.bushor.2018.03.007
[15]. Kahneman, D. (2011). Thinking, fast and slow. Farrar, Straus and Giroux. https://www.hachettebookgroup.com/titles/daniel-kahneman/thinking-fast-and-slow/9780374533557/
[16]. Kahneman, D., Sibony, O., & Sunstein, C. R. (2021). Noise: A flaw in human judgment. Little, Brown Spark. https://www.hachettebookgroup.com/titles/daniel-kahneman/noise/9780316451406
[17]. Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15-25. https://doi.org/10.1016/j.bushor.2018.08.004
[18]. Kazi Rakib Hasan, S. (2026). Artificial Intelligence in Project and Business Operations Management in US: A Systematic Review of Decision-Support Models. American Journal of Data Science and Analytics, 7(01), 45-86. https://doi.org/10.63125/z6c3b737
[19]. Lebovitz, S., Levina, N., & Lifshitz-Assaf, H. (2021). Is AI ground truth really true? The dangers of training and evaluating AI tools based on experts' know-what. MIS Quarterly, 45(3), 1501-1526. https://doi.org/10.25300/MISQ/2021/16564
[20]. Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. Organizational Behavior and Human Decision Processes, 151, 90-103. https://doi.org/10.1016/j.obhdp.2018.12.005
[21]. McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. Harvard Business Review, 90(10), 60-68. https://hbr.org/2012/10/big-data-the-management-revolution
[22]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use he Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. American Journal of Scholarly Research and Innovation, 4(01), 202-220. https://doi.org/10.63125/pbjxp014
[23]. Md Mesbaul, H. (2023). A Meta-Analysis of Lean Merchandising Strategies In Fashion Retail: Global Insights From The Post-Pandemic Era. Review of Applied Science and Technology, 2(04), 94-123. https://doi.org/10.63125/y8x4k683
[24]. Md Mesbaul, H. (2025). A Framework-Based Meta-Analysis Of Artificial Intelligence-Driven ERP Solutions For Circular And Sustainable Supply Chains. International Journal of Scientific Interdisciplinary Research, 6(1), 327-367. https://doi.org/10.63125/n6k7r711
[25]. Md Mesbaul, H. (2026). AI-Driven Smart Hybrid Manufacturing for Enhanced Sustainability and Production Performance in U.S. Industry. American Journal of Data Science and Analytics, 7(06), 226-243. https://doi.org/10.63125/hg8tvk79
[26]. Md Mostafizur, R. (2025). Data-Driven Graph Neural Network Models for Detecting Fraudulent Insurance Claims In Healthcare Systems. American Journal of Interdisciplinary Studies, 6(1), 263-294. https://doi.org/10.63125/pmqa1e33
[27]. Md Mostafizur, R., Omar Muhammad, F., & Sheratun Noor, J. (2025). Data Privacy in Business Intelligence Systems: Ensuring Compliance In HRIS And Enterprise Platforms. International Journal of Scientific Interdisciplinary Research, 6(1), 97-136. https://doi.org/10.63125/527rnx08
[28]. Md Syeedur, R., & Sharmin, R. (2025). A Data-Driven Study on the use of Small Language Models & Large Language Models for Interpreting Complex Industrial Data and Deriving Actionable Outcome. American Journal of Data Science and Analytics, 6(11), 01-19. https://doi.org/10.63125/5vyhgs98

[29]. Md Syeedur, R., & Sharmin, R. (2026a). Generative PLM: Utilizing Large Language Models for Automated Engineering Change Management and Requirements Traceability: A Case Study in Smart Manufacturing. American Journal of Interdisciplinary Studies, 7(02), 53-72. https://doi.org/10.63125/xbj93w89

[30]. Md Syeedur, R., & Sharmin, R. (2026b). A Runtime Activity-Aware Framework for Dynamic Floating License Reclamation in Enterprise CAD Environments Study in Smart Manufacturing. American Journal of Advanced Technology and Engineering Solutions, 6(01), 690-716. https://doi.org/10.63125/adwrax90

[31]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. International Journal of Business and Economics Insights, 1(4), 70-102. https://doi.org/10.63125/dyrpc387

[32]. Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. ACM Computing Surveys, 54(6), 1-35. https://doi.org/10.1145/3457607

[33]. Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. British Journal of Management, 30(2), 272-298. https://doi.org/10.1111/1467-8551.12343

[34]. Mohammad Shoriful Hossan, S. (2021). Reducing Worker Exposure and Electrical Failure Risk in Brownfield Manufacturing Facilities After COVID-Era Maintenance Delays. Review of Applied Science and Technology, 6(1), 263–279. https://doi.org/10.63125/cm1c2c20

[35]. Mst Shurovi, A. (2024). Machine Learning Models for Bank Reconciliation Anomaly Detection in High-Volume Financial Transactions. American Journal of Data Science and Analytics, 5(12), 314-354. https://doi.org/10.63125/mmwb6467

[36]. Mst Shurovi, A. (2026). AI-Driven Accounts Payable and Receivable Automation for Operational Risk Mitigation in U.S. SMEs: A Systematic Review (2018–2026). American Journal of Interdisciplinary Studies, 7(01), 536-577. https://doi.org/10.63125/x1yzwc45

[37]. Muhammad Zahidul, I. (2024). Assessment of Data Integrity Gaps and Preventive Strategies in QC Laboratories in Compliance with FDA and CGMP Expectations. American Journal of Scholarly Research and Innovation, 3(01), 243–291. https://doi.org/10.63125/a3xjb608

[38]. Muhammad Zahidul, I. (2025). Development of a Dashboarding and Visualization Framework For Pharmaceutical Brand Performance Analytics Using Tableau and Python. American Journal of Interdisciplinary Studies, 6(3), 351-393. https://doi.org/10.63125/e6djq308

[39]. Muhammad Zahidul, I. (2026). Implementation of a Predictive-Analytics Framework for Pharmaceutical Demand Forecasting and Supply-Chain Resilience in U.S. Healthcare Markets. American Journal of Data Science and Analytics, 7(01), 166–193. https://doi.org/10.63125/zjpe3a17

[40]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied Data-Analytics Approaches to Cardiovascular Drug-Utilization Patterns: An Empirical Study Using Real-World Pharmaceutical Sales Data. American Journal of Data Science and Analytics, 3(12), 89-129. https://doi.org/10.63125/7xgryf71

[41]. Mukut Kanti, B. (2025). Lifecycle Carbon Reduction and Net Zero Pathway Modeling Using LEED, EDGE, and SBTI Frameworks in Developing Economy Industrial Buildings. American Journal of Interdisciplinary Studies, 6(3), 306-350. https://doi.org/10.63125/tnneth75

[42]. Pfeffer, J., & Sutton, R. I. (2006). Evidence-based management. Harvard Business Review, 84(1), 62-74. https://hbr.org/2006/01/evidence-based-management

[43]. Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. Big Data, 1(1), 51-59. https://doi.org/10.1089/big.2013.1508

[44]. Redman, T. C. (1998). The impact of poor data quality on the typical enterprise. Communications of the ACM, 41(2), 79-82. https://doi.org/10.1145/269012.269025

[45]. Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence, 1(5), 206-215. https://doi.org/10.1038/s42256-019-0048-x

[46]. Sharif Md Yousuf, B., Md Shahadat, H., Saleh Mohammad, M., Mohammad Shahadat Hossain, S., & Imtiaz, P. (2025). The Green Hydrogen Blueprint: Optimizing America's Clean Energy Future. American Journal of Data Science and Analytics, 6(10), 43-69. https://doi.org/10.63125/y9b1k470

[47]. Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations. European Journal of Information Systems, 23(4), 433-441. https://doi.org/10.1057/ejis.2014.17

[48]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. American Journal of Data Science and Analytics, 5(10), 01-47. https://doi.org/10.63125/ehk4mt02

[49]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2025). Telemedicine And Remote Patient Monitoring for Preventing Risk and Chronic Disease Management in Underserved Communities. American Journal of Health and Medical Sciences, 6(04), 01–42. https://doi.org/10.63125/y0e9dc38

[50]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2026). STI and HIV Prevention Through Public Health Digital Twins: A Framework for Personalized Prevention and Adaptive Disease Intervention. American Journal of Scholarly Research and Innovation, 5(01), 284–326. https://doi.org/10.63125/rjgna882

[51]. Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. California Management Review, 61(4), 66-83. https://doi.org/10.1177/0008125619862257

[52]. Shrivastava, P., Mitroff, I. I., Miller, D., & Miglani, A. (1988). Understanding industrial crises. Journal of Management Studies, 25(4), 285-303. https://doi.org/10.1111/j.1467-6486.1987.tb00466.x
[53]. Simon, H. A. (1997). Administrative behavior (4th ed.). Free Press. https://www.simonandschuster.com/books/Administrative-Behavior-4th-Edition/Herbert-A-Simon/9780684835822
[54]. Tonay, P., Md Maruf, I., & Al, A. (2024). Artificial Intelligence-Based Decision Support Systems and Managerial Performance. American Journal of Advanced Technology and Engineering Solutions, 4(04), 154-184. https://doi.org/10.63125/wmz8dc67
[55]. Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. Science, 185(4157), 1124-1131. https://doi.org/10.1126/science.185.4157.1124
[56]. Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., ... van Mulbregt, P. (2020). SciPy 1.0: Fundamental algorithms for scientific computing in Python. Nature Methods, 17(3), 261-272. https://doi.org/10.1038/s41592-019-0686-2
[57]. Wachter, S., Mittelstadt, B., & Floridi, L. (2017). Why a right to explanation of automated decision-making does not exist in the General Data Protection Regulation. International Data Privacy Law, 7(2), 76-99. https://doi.org/10.1093/idpl/ipx005
[58]. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356-365. https://doi.org/10.1016/j.jbusres.2016.08.009
[59]. Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. Journal of Management Information Systems, 12(4), 5-33. https://doi.org/10.1080/07421222.1996.11518099
[60]. Weick, K. E., & Sutcliffe, K. M. (2007). Managing the unexpected: Resilient performance in an age of uncertainty (2nd ed.). Jossey-Bass. https://www.wiley.com/en-us/Managing+the+Unexpected%3A+Resilient+Performance+in+an+Age+of+Uncertainty%2C+2nd+Edition-p-9780787996499