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A Review on Understanding Data Governance Failures in Analytics Systems: Insights from Expert Interviews and Root-Cause Thematic Coding

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Abstract

This study investigates the persistent problem of weak analytics outcomes in organizations despite substantial investment in data platforms, dashboards, and business intelligence tools, arguing that the deeper source of breakdown often lies in data governance failure rather than in technology alone. The purpose of the research was to examine how specific governance failures affect analytics system effectiveness and to identify which failure dimensions are most damaging in organizational settings. Using a quantitative, cross-sectional, case-based design, the study collected survey data from cloud and enterprise analytics cases through 250 distributed questionnaires, of which 214 usable responses were analyzed, yielding an effective response rate of 85.6%. The sample consisted of professionals directly involved in analytics and data processes, including Data/BI analysts, IT and systems staff, compliance officers, and reporting managers. The key independent variables were Data Quality Failure, Accountability and Ownership Failure, Policy and Compliance Failure, Access-Control and Security Failure, and Metadata and Documentation Failure, while the dependent variable was Analytics System Effectiveness. The analysis plan combined descriptive statistics, Cronbach's alpha reliability testing, Pearson correlation analysis, and multiple regression modeling in SPSS. The findings showed high perceived exposure across all governance failure dimensions, with Data Quality Failure recording the highest mean score ($M = 4.08$, $SD = 0.71$), followed by Metadata and Documentation Failure ($M = 4.02$, $SD = 0.69$), while Analytics System Effectiveness remained comparatively low ($M = 2.64$, $SD = 0.83$). Reliability was strong across constructs, with Cronbach's alpha ranging from 0.82 to 0.91 and an overall instrument alpha of 0.93. Correlation results revealed significant negative relationships between governance failures and analytics effectiveness, led by Data Quality Failure ($r = -0.68$, $p < .01$) and Metadata and Documentation Failure ($r = -0.64$, $p < .01$). The regression model was statistically significant, $F(5,208) = 46.37$, $p < .001$, explaining 52.7% of the variance in analytics system effectiveness (Adjusted $R^2 = 0.527$). Data Quality Failure emerged as the strongest predictor (beta = -0.31, $p < .001$), followed by Metadata and Documentation Failure (beta = -0.27, $p < .001$). The study implies that organizations seeking more trustworthy and decision-supportive analytics should prioritize governance reforms in data quality, documentation, accountability, and policy enforcement rather than relying only on technical upgrades.

Keywords

Data Governance Failure, Analytics System Effectiveness, Data Quality, Metadata And Documentation, Quantitative Cross-Sectional Study;

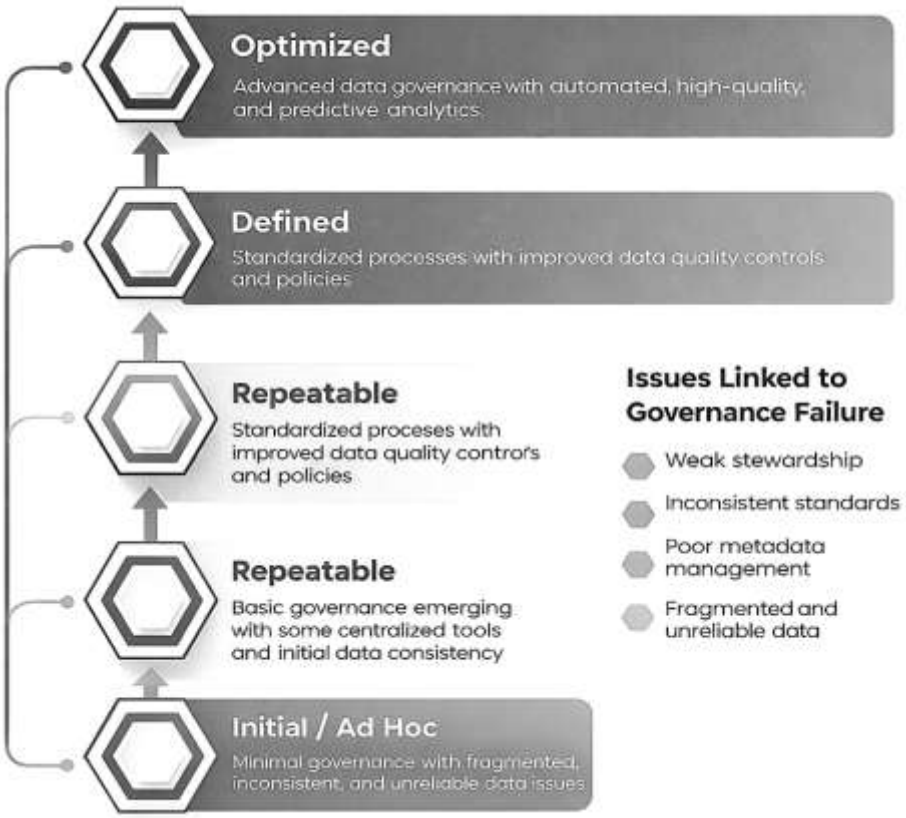
INTRODUCTION

Data governance is generally understood as the exercise of authority, control, and shared decision-making over the management of data assets, while analytics systems refer to socio-technical environments through which organizations collect, integrate, process, model, visualize, and interpret data for operational and strategic decision-making purposes (Al-Ruithe & Benkhelifa, 2017). Within the broader information governance literature, governance has been treated as a concept that extends far beyond technical administration because it also includes policies, standards, decision rights, stewardship roles, monitoring procedures, and organizational routines that regulate the creation, maintenance, access, protection, and use of information resources across institutional settings (Li et al., 2021). This subject carries substantial international significance because organizations across finance, healthcare, retail, logistics, government, education, telecommunications, and digital service sectors now rely on complex data infrastructures that often cut across organizational and jurisdictional boundaries (Popovič et al., 2012). Data has become a strategic resource in the global economy, yet its value is inseparable from the institutional arrangements that determine who owns it, who is responsible for its quality, how it is secured, how it is interpreted, and how it can be legitimately used (Al-Ruithe & Benkhelifa, 2020). For this reason, data governance should not be viewed as a secondary administrative layer attached to information systems, because it functions as a foundational condition for analytical trustworthiness, accountability, compliance, and coordinated organizational action (Işık et al., 2013). Important work in this area has identified major governance decision domains such as data principles, metadata, data quality, access, and lifecycle management priorities, thereby showing that governance defines the structural conditions under which data can be managed as an enterprise asset rather than as a fragmented technical resource. Governance has also been linked to organizational concerns surrounding value, risk, and cost in large-scale data environments, which demonstrates that authority structures around data strongly influence whether analytics can be used in a disciplined, transparent, and auditable manner (Al-Ruithe et al., 2019). In the context of analytics systems, governance failures commonly appear in the form of weak stewardship, fragmented accountability, inconsistent standards, unreliable source data, inadequate metadata, poor documentation, and ambiguous access rules, all of which undermine the credibility of analytic outputs (Alhassan et al., 2016). These failures matter internationally because the expansion of digitized organizational systems has made institutions increasingly dependent on data-intensive coordination while simultaneously exposing them to significant performance, compliance, service quality, and trust-related risks when governance structures are weak (Al-Ruithe et al., 2016).

Within scholarly research, data governance has been conceptualized as a multidimensional organizational and managerial construct rather than as a narrow technical control function. A substantial stream of literature has described governance activities as including policy formulation, role assignment, stewardship design, metadata administration, architecture alignment, compliance monitoring, and data quality management, thereby suggesting that governance is best understood as a coordinated set of organizational practices rather than a single intervention (Alhassan et al., 2019). Comparative work between scientific and practice-oriented literature has further shown that the field has evolved through both academic theorization and organizational experimentation, with each stream contributing to a growing understanding of how responsibility structures must be formalized around enterprise data resources (Kooper et al., 2011). Research focused on critical success factors has also emphasized the importance of executive support, role clarity, communication, accountability, organizational fit, and sustained managerial commitment in making data governance operationally effective. A related conceptual contribution framed information governance as an enabling institutional concept that helps organizations connect strategic objectives with information responsibilities across functions and hierarchical levels, thereby reinforcing the view that information management requires governance arrangements that coordinate decision rights and accountability rather than isolated technical fixes. This perspective is highly relevant to analytics systems because analytical outputs rarely originate from a single application, team, or department (Batini et al., 2009). Instead, they depend on interconnected flows of source data, transformation rules, definitions, ownership structures, access rights, and interpretive practices distributed across multiple organizational actors. Empirical work in public asset management has demonstrated that data governance directly influences data-driven

decision-making because better coordination of governance structures improves consistency between data practices and managerial action. Similar evidence from the health information exchange domain has shown that governance and data-sharing agreements are essential for coordination across multiple institutions when shared information infrastructures are involved. These studies collectively establish that governance is institutional in character because it embeds authority, accountability, process discipline, and shared meaning into data work (Abraham et al., 2019). When governance arrangements are weak or fragmented, organizations experience more than routine technical inefficiencies; they encounter systemic weaknesses in the production, interpretation, legitimacy, and use of analytical evidence across decision environments.

Figure 1: Data Governance Maturity Stages in Analytics Systems



Analytics systems have also been widely examined as organizational capabilities that combine data resources, technological infrastructures, analytical models, decision processes, and managerial contexts to support evidence-based action (Alhassan et al., 2018). Research on business intelligence and analytics has consistently shown that successful analytics systems depend on far more than software acquisition or technical sophistication. Foundational work on business intelligence success identified critical factors such as strong data foundations, management commitment, user participation, technical quality, and alignment between the system and organizational processes. Subsequent research connected business intelligence system success to organizational maturity and culture, showing that analytics becomes effective only when outputs are absorbed into broader processes of analytical decision-making and organizational learning (Allen et al., 2014; Md. Morshedul et al., 2022; Md. Nazmul & Amena Begum, 2022). Related work further demonstrated that business intelligence success depends on the interaction between BI capabilities and the decision environment, indicating that analytical value is shaped by organizational conditions as much as by technological functionality. This line of inquiry was later extended through research that emphasized implementation quality, governance support, and the interdependence of technical and organizational dimensions in successful business intelligence systems. Other studies connected business intelligence effectiveness to corporate performance management, thereby showing that the reliability and usability of analytical outputs

influence broader organizational control processes and performance evaluation practices (Ferdous Ara, 2021; Khatri & Brown, 2010; Mahfuj Ahmed & Md. Hasan Or, 2021). Research on adoption stages also found that organizations move unevenly in their analytics journeys and that the conditions that support system use differ depending on structural readiness, resource availability, and organizational maturity. This body of literature provides strong grounding for the current study because it demonstrates that analytics systems are not self-validating engines of organizational knowledge (Aditya & Mohammad Robel, 2022; Chen et al., 2015; Mohammad Robel & Md. Morshedul, 2021). Their outputs depend on the quality, consistency, traceability, interpretability, and governance of the data they process. An organization may possess advanced dashboards, reporting tools, visualization layers, predictive models, and business intelligence applications, yet still produce weak analytical outcomes when governance structures fail to define common meanings, maintain source-data integrity, document transformations, or enforce stewardship responsibilities. Governance failure therefore becomes central to understanding why analytics systems often underperform in practice even when technical infrastructures appear sophisticated (Dey & Kumar, 2010).

A major literature stream that further supports the study of governance failure concerns data quality and information quality, since analytics systems are only as credible as the data environments from which their outputs are generated. Research on data quality assessment and improvement has shown that quality management is a systematic organizational activity involving the identification, measurement, monitoring, and correction of quality problems across the data lifecycle. Related scholarship has emphasized that data quality must be understood in context because quality is judged in relation to user needs, meanings, interpretive frames, and task requirements rather than as an abstract attribute detached from use (Brous et al., 2016; Istiaq & Nusrat, 2022; Md Khaled & Hisham, 2022). Work on information products has similarly argued that data quality should be reassessed in relation to the usefulness and reliability of downstream outputs, which is especially important in analytics systems where raw data is transformed into reports, dashboards, and predictive insights for managerial consumption. These studies indicate that incompleteness, inconsistency, ambiguity, untimeliness, and poor contextual fit can degrade analytical interpretation even when large quantities of data are available (Côrte-Real et al., 2019). From a governance perspective, these problems rarely emerge in an entirely random or isolated manner (Md Mehedi & Md, 2022; Md. Mainuddin & Palash Chandra, 2022). They are often associated with weak stewardship, absent or poorly enforced standards, inadequate metadata, fragmented ownership, poor documentation, and insufficient oversight of how data is collected, transformed, and interpreted across organizational units. Governance has therefore been closely tied to risk management in large data environments because the pursuit of data value without corresponding controls over integrity, accountability, and meaning can create serious exposure for organizations that depend on analytics for coordination and decision-making (Janssen et al., 2020). More recent work has also linked reliable governance directly to trustworthy artificial intelligence, which reinforces the wider principle that trust in data-driven systems depends on how data is organized, controlled, and made accountable across institutional contexts. In analytics settings, governance failure can therefore be observed not only in policy noncompliance or weak access control, but also in reduced interpretability, limited verifiability, and declining confidence in the outputs that analytical systems generate. When data definitions differ across functions, lineage is weakly documented, or ownership is unclear, analytical findings become harder to trust, harder to validate, and harder to translate into sound organizational action (Richards et al., 2019).

The international significance of governance failure becomes especially visible in distributed, multi-organizational, cloud-based, and inter-organizational information environments where data infrastructures are shared across institutional boundaries (Tallon, 2013). Evidence from community-wide health information exchange has shown that governance arrangements and data-sharing agreements are indispensable for coordination across organizations, especially when confidentiality, common standards, access rights, and accountability mechanisms must be negotiated among multiple stakeholders. Research in public asset management has similarly demonstrated that data governance affects data-driven decision processes in measurable ways, illustrating that governance quality shapes operational coordination and managerial action well beyond the boundaries of a single application or database. In cloud environments, governance challenges become even more complex because control

over data is often distributed across service layers, virtual infrastructures, and multiple organizational actors (Md. Shahinur & Md. Sultan, 2022; Tanjina Binte & Md. Hasan Or, 2022; Watts et al., 2009). Conceptual work on cloud data governance has therefore argued that such settings require governance arrangements capable of addressing distributed control, service accountability, privacy, and security responsibilities in a coherent manner. Research on barriers and critical success factors for cloud data governance implementation has identified organizational, technical, and regulatory obstacles that complicate efforts to maintain accountability and control over shared data resources. A systematic review in this area further consolidated the literature by showing that cloud data governance repeatedly involves concerns around privacy, trust, compliance, ownership, and operational control across virtualized and distributed environments. An additional empirical contribution modeled enabling factors for implementing cloud data governance in the public sector and reinforced the view that governance effectiveness depends on institutional support, procedural clarity, and technological capability working together rather than independently (Popovič et al., 2018). These concerns have also been extended into the field of artificial intelligence, where trustworthy AI has been directly linked to the organization and governance of data, thereby underscoring that legitimacy in automated or analytics-intensive systems begins with how data is structured, controlled, and rendered accountable. Collectively, these studies show that governance failure is not a narrow local inconvenience confined to one department. It is a globally relevant systems problem that affects how data moves across institutions, how responsibility is allocated, and how the outputs of analytics and automated reasoning are judged as legitimate in environments shaped by technical, organizational, and legal complexity (Yeoh & Koronios, 2010).

The importance of governance in analytics systems is also reinforced by research on organizational value creation, performance outcomes, and decision quality in business intelligence and big data analytics. Studies in supply chain management have shown that the use of big data analytics contributes to value creation when analytics capabilities are meaningfully embedded into managerial processes and coordination routines (Amena Begum & Mst Kaniz, 2023; Ferdous Ara & Beatrice Onyinyechi, 2023). Research on firm-level performance has similarly reported that big data analytics can enhance high-value business performance, thereby supporting the argument that analytical capability can become a source of organizational advantage under the right structural conditions. Work on the drivers of big data analytics value has added that value realization depends on a broader organizational context rather than on the mere possession of data or analytical technologies, which means that organizational arrangements strongly mediate whether analytics translates into practical benefit. This position is directly relevant to governance because data value cannot be separated from the conditions that make information reliable, interpretable, legitimate, and usable within organizations. Research focused specifically on decision-making quality has also found that the use of big data analytics contributes to better decision quality, thereby strengthening the case that analytics effectiveness must be examined not only through technical performance but also through the quality of the data and controls that support its use (Puklavec et al., 2018). Earlier business intelligence studies had already indicated similar themes by linking analytical decision-making to BI maturity, organizational culture, BI capabilities, decision context, and performance management practices. Taken together, this literature shows that analytics systems may support value creation and informed decision-making, yet this support depends on conditions that make data trustworthy, accessible, coherent, and actionable across organizational processes. Governance enters this discussion because value in analytics cannot be sustained where reports are generated from inconsistent data definitions, undocumented transformations, weak stewardship, poor access controls, or fragmented ownership arrangements (Islam & Aditya, 2023; Mahfuj Ahmed & Md. Mehedi, 2023; Yeoh & Popovič, 2016). Reports may be technically produced, dashboards may appear sophisticated, and predictive models may generate outputs, yet the underlying evidence base may still remain vulnerable to serious governance weaknesses that reduce trust, usability, and managerial legitimacy. The literature on analytics value therefore provides strong justification for studying governance failures directly, since any claim about the usefulness of analytics is inseparable from the organizational conditions under which data is managed, verified, interpreted, and accepted as credible evidence for decision-making (Puklavec et al., 2018).

Across the existing literature, there is now substantial knowledge about what data governance is, which activities it includes, how analytics systems generate value, and what organizational conditions support business intelligence and data-driven decision-making. The field has benefited from conceptual syntheses, structured reviews, theory-building efforts, and empirical examinations of governance activities and success factors, all of which have clarified the importance of governance as an organizational capability and institutional arrangement. Research on business intelligence and analytics has also explained many of the conditions associated with system success, including maturity, culture, capabilities, implementation quality, and decision environment. Additional work has connected analytics use to firm performance, value creation, and decision quality, further reinforcing the managerial importance of analytical systems in modern organizations. Even with this extensive body of scholarship, the literature remains less direct in treating data governance failure itself as a measurable and multidimensional organizational condition within analytics systems (Alhassan et al., 2016). Much of the prior work has approached governance as a success enabler, an institutional framework, or a managerial capability. Comparatively less attention has been devoted to decomposing governance failure into specific forms such as data quality weakness, metadata insufficiency, ownership ambiguity, access-control inconsistency, weak documentation, and policy-enforcement gaps, and then examining these in relation to analytics system effectiveness through a quantitative and case-based approach (Batini et al., 2009). This unresolved area is especially important because analytics systems are frequently evaluated in terms of adoption, maturity, performance, or strategic value, while the organizational sources of unreliable outputs may remain distributed across departments, routines, data structures, and accountability arrangements. A failure-oriented perspective makes it possible to treat governance not only as an idealized organizational design, but also as a field of vulnerability that shapes the credibility of reports, dashboards, metrics, and model-based insights. Such an orientation is particularly relevant in analytics environments where the reliability of outputs depends on the governance integrity of the data ecosystem from which they are generated and through which they are interpreted by organizational actors (Al-Ruithe & Benkhelifa, 2017).

Background of the Study

The background of this study is rooted in the increasing dependence of modern organizations on analytics systems for planning, monitoring, forecasting, evaluation, and strategic decision-making across a wide range of sectors. In today's digital environment, data is no longer viewed as a passive record of organizational activities but as a valuable institutional asset that directly shapes performance, competitiveness, accountability, and operational efficiency. Analytics systems play a central role in converting raw, scattered, and often complex datasets into meaningful outputs such as reports, dashboards, predictive models, trend analyses, and performance indicators that support managerial judgment and guide institutional action. These systems are now deeply integrated into functions such as customer intelligence, financial reporting, risk assessment, logistics coordination, healthcare planning, fraud detection, and policy monitoring. As a result, organizations across both public and private domains increasingly rely on data-driven technologies to improve accuracy, speed, and consistency in decision-making processes. The usefulness of analytics systems, however, is not determined by technology alone. Their effectiveness depends heavily on the quality, consistency, accessibility, security, ownership, and interpretability of the data that enters and moves through them. This condition makes data governance an essential organizational function. Data governance provides the formal structures, responsibilities, policies, standards, and control mechanisms that regulate how data is defined, collected, stored, shared, protected, and used throughout its lifecycle. When these governance arrangements are strong, analytics systems are more likely to generate reliable, transparent, and trusted outputs that can support sound decisions. When they are weak, organizations may experience duplicated records, conflicting definitions, inconsistent reports, missing documentation, low accountability, poor-quality data, and uncertainty about who is responsible for maintaining data integrity. In many cases, analytics system failure is not caused by the absence of tools or software, but by governance breakdowns that silently disrupt the data environment on which these tools depend. These failures may appear through weak stewardship, fragmented control, limited compliance monitoring, uncoordinated departmental practices, or a lack of clear ownership over critical data resources. As organizations continue to expand their use of analytics for operational and strategic

purposes, the risks associated with poor governance become more significant. These risks can affect decision accuracy, regulatory readiness, system credibility, organizational trust, and overall performance. This study therefore arises from the need to understand data governance failures as serious organizational conditions that influence the effectiveness of analytics systems and the credibility of the insights they are expected to produce.

Problem Statement

The problem addressed in this study arises from the growing contradiction between the widespread adoption of analytics systems and the continuing presence of unreliable, inconsistent, and weakly trusted analytical outputs in many organizations. Across institutions, analytics platforms are introduced with the expectation that they will improve decision-making accuracy, strengthen planning, enhance operational control, and generate valuable insights from organizational data. In practice, however, many organizations continue to struggle with reporting inconsistencies, low confidence in dashboards, duplicated records, incompatible data definitions, missing documentation, weak access controls, and unclear ownership of critical data assets. These issues reduce the credibility and usefulness of analytics systems even when substantial investments have been made in software, infrastructure, and digital transformation. A central concern is that the failure of analytics systems is often interpreted as a technical issue, while the deeper organizational causes may actually lie in weak data governance arrangements. Where governance structures are fragmented, responsibilities are poorly assigned, standards are inconsistently enforced, and stewardship roles are not clearly established, the data environment becomes unstable and the outputs of analytics systems become more difficult to trust. This creates a serious challenge for organizations that depend on data-driven evidence for strategy, compliance, resource allocation, risk management, and performance evaluation. The problem is made more significant by the fact that governance failures often remain hidden behind seemingly functional systems. An organization may have dashboards, data warehouses, and business intelligence tools in place, yet the underlying data may still be compromised by poor control, weak accountability, or inconsistent interpretation across departments. Such failures can distort analysis, mislead managers, delay responses, and reduce organizational confidence in data-driven processes. Another aspect of the problem is the limited attention given to governance failure as a measurable, multidimensional condition within analytics environments. Existing discussions frequently emphasize governance frameworks, best practices, or success factors, but give less direct attention to how specific failures in quality control, policy enforcement, ownership, security, and documentation combine to weaken analytics effectiveness. This study is therefore motivated by the need to identify and examine the major dimensions of data governance failure within analytics systems and to determine how these failures affect the reliability, trustworthiness, and effectiveness of analytical outputs in organizational settings.

Objective of the Study

The objective of this study is to examine how failures in data governance influence the effectiveness of analytics systems within organizational contexts and to provide a structured understanding of the governance conditions that weaken the credibility of analytical outputs. More specifically, the study seeks to move beyond the general assumption that analytics problems are mainly technical and instead focus on the organizational roots of weak analytics performance. The intention is to identify the major forms of governance failure that emerge within analytics environments, such as poor data quality management, unclear ownership and accountability, weak policy enforcement, inadequate documentation, fragmented stewardship, and insufficient access control. By focusing on these dimensions, the study aims to establish whether governance failure can be treated as a measurable and analytically significant factor in explaining why some analytics systems fail to produce reliable, useful, and trusted results. Another core objective is to assess the relationship between governance weaknesses and key indicators of analytics system effectiveness, including the reliability of outputs, confidence in reports and dashboards, consistency of data interpretation, and support for sound decision-making. This objective is important because organizations often rely on analytics systems to guide strategic action, yet the actual usefulness of these systems depends on whether the underlying data environment is governed in a disciplined and coordinated manner. The study also aims to determine which governance failure dimensions have the strongest predictive influence on analytics system breakdown,

thereby making it possible to distinguish between routine governance weaknesses and the root failure factors that are most damaging in practice. In addition, the study intends to provide a case-based quantitative assessment that can support a clearer understanding of how governance-related problems operate across real organizational settings rather than only in abstract conceptual terms. By doing so, the research seeks to generate evidence that can help explain how governance failure affects the operational and strategic value of analytics systems. The overall objective is therefore not only to describe governance problems, but also to analyze their statistical relationships, test their influence on analytics outcomes, and offer a more focused explanation of how organizational weaknesses in governing data can undermine the systems that are expected to transform data into dependable insight.

Research Hypotheses

The research hypotheses of this study are developed to test the assumption that failures in data governance have a direct and measurable effect on the effectiveness of analytics systems. Since the study is quantitative, cross-sectional, and case-study based, the hypotheses serve as formal statements that connect the core dimensions of governance failure with the main outcomes associated with analytics system performance. The logic behind these hypotheses is that analytics systems do not operate independently of the organizational conditions that shape the quality, control, accessibility, and interpretation of data. When governance is weak, data may become inconsistent, poorly documented, insecure, or weakly owned, and such conditions are likely to reduce the reliability and trustworthiness of analytic outputs. On this basis, the study proposes that data quality failure will have a significant negative relationship with analytics system effectiveness because poor-quality data can weaken reporting accuracy, reduce confidence in analysis, and limit the usefulness of system outputs. The study also proposes that accountability and ownership failure will negatively affect trust in analytics outputs because unclear responsibility for data management often creates confusion, weakens stewardship, and limits corrective action when errors occur. A further hypothesis is that policy and compliance failure will negatively influence analytics system reliability, since weak enforcement of data standards and governance rules can produce inconsistent practices across departments and reduce the overall integrity of the analytics environment. Another hypothesis proposes that access-control and security failure will negatively affect decision-making effectiveness, because insecure or poorly controlled data environments can reduce confidence in the legitimacy, safety, and proper use of analytical information. The study also hypothesizes that metadata and documentation failure will have a negative effect on analytics usability and consistency, since poor documentation can make data harder to interpret, validate, and apply correctly across functions. Finally, the study proposes an overall predictive hypothesis stating that the combined dimensions of data governance failure significantly explain analytics system breakdown. These hypotheses are central to the study because they translate broad governance concerns into testable statistical relationships and provide a structured basis for determining whether governance failure is not only conceptually important but also empirically significant in shaping the performance, trustworthiness, and decision value of analytics systems.

Significance of the Research

The significance of this research can be understood from several important perspectives:

i. Academic significance: This study contributes to the growing body of knowledge on data governance and analytics systems by focusing specifically on governance failure rather than governance success. Many studies discuss frameworks, maturity models, and best practices, yet fewer studies examine how concrete governance breakdowns weaken analytics effectiveness. This research therefore adds conceptual and empirical value by treating governance failure as a measurable organizational condition.

ii. Methodological significance: The study offers a quantitative and case-based approach for examining data governance failure in analytics environments. By using structured variables, Likert-scale measurement, descriptive statistics, correlation analysis, and regression modeling, the research creates a systematic way to test governance-related assumptions that are often discussed only in conceptual or managerial terms.

iii. Organizational significance: The study is significant for organizations that rely on analytics systems for operational and strategic decisions. It helps reveal that weak analytical outcomes may not always be caused by software limitations, but by failures in ownership, quality control, documentation,

security, and policy enforcement. This can support a more accurate diagnosis of why analytics systems underperform.

iv. Managerial significance: Managers, data stewards, and governance officers can benefit from the findings by gaining a clearer understanding of which governance failures most strongly reduce trust in reports, dashboards, and analytical outputs. This can help management prioritize corrective actions and strengthen areas of governance that have the highest operational impact.

v. Practical significance: The research provides a structured basis for improving the reliability, usability, and trustworthiness of analytics systems. It can assist organizations in identifying vulnerable governance areas and in designing more coordinated data practices that support consistent decision-making and stronger institutional control.

vi. Policy significance: The study is also significant for policy development because it highlights the importance of formal governance rules, accountability structures, and control procedures in shaping data integrity. This may support internal governance reform and strengthen compliance-related thinking within organizations that operate in regulated or high-risk environments.

vii. Strategic significance: At a broader level, the study is significant because analytics systems increasingly influence performance management, planning, risk control, and competitive positioning. Understanding governance failure helps organizations protect the strategic value of data and improve the credibility of the insights that guide long-term action.

LITERATURE REVIEW

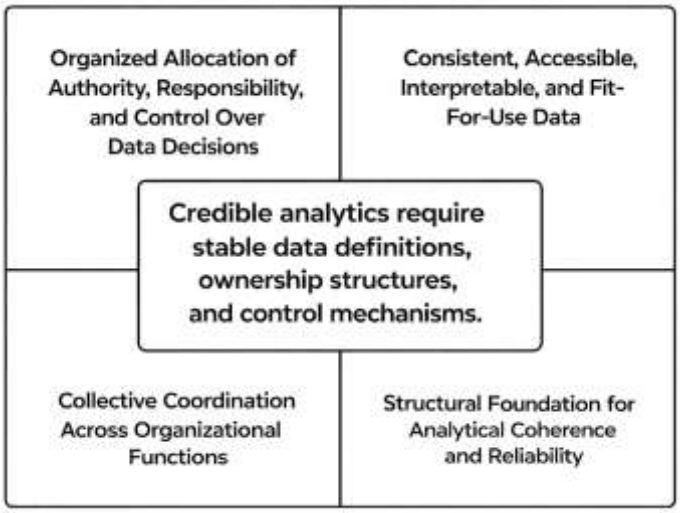
The literature review for this study is centered on the relationship between data governance and the effectiveness of analytics systems, with particular attention to how governance failure undermines the reliability, trustworthiness, and operational value of analytical outputs. In modern organizations, analytics systems have become central instruments for transforming raw data into actionable information used for planning, performance measurement, forecasting, risk assessment, and strategic decision-making. At the same time, the ability of these systems to produce meaningful and dependable outputs is closely tied to how data is governed across its lifecycle. This means that the quality of analytics cannot be understood solely in technical terms, because organizational rules, policies, standards, ownership structures, stewardship practices, and accountability mechanisms strongly influence whether data remains consistent, interpretable, secure, and usable. The literature therefore provides an essential foundation for understanding why governance should be treated as a central condition of analytics effectiveness rather than as a secondary administrative issue. Existing scholarship has explained that data governance involves coordinated decision rights and control mechanisms over how data is defined, collected, stored, shared, protected, and used within institutions. Related research on business intelligence and analytics systems has shown that successful analytics depends on more than technological capability, since organizational maturity, management support, data quality, and process integration all shape the value that analytics can create. The literature also indicates that organizations often experience failures in data quality, policy enforcement, metadata management, access control, and role clarity, and these failures can directly weaken trust in reports, dashboards, and analytical models. For this reason, a focused review of prior studies is necessary to clarify the key concepts, theoretical foundations, and empirical findings relevant to the present research. This literature review is designed to establish the scholarly context of the study by examining the meaning of data governance in analytics settings, the common forms of governance failure, the consequences of those failures for analytics performance, the theoretical framework that explains the interaction of human, organizational, and technical factors, and the conceptual framework that links the independent and dependent variables of the study. Through this structure, the review builds the intellectual basis for investigating data governance failure as a measurable and significant factor in analytics system breakdown.

Data Governance in Analytics Systems

Data governance in analytics systems can be understood as the organized allocation of authority, responsibility, and control over data-related decisions so that analytical processes operate on data that is consistent, interpretable, accessible, and fit for organizational use. In analytics environments, data does not move through a single linear pipeline. It is captured from multiple operational sources, transformed across technical layers, interpreted by different functional groups, and then translated into

dashboards, reports, predictive outputs, and managerial indicators. This complexity means that analytics systems require more than computational tools and storage capacity; they require a clear governance structure that establishes who defines core data elements, who resolves quality issues, who approves standards, and who is accountable for the integrity of data across its lifecycle. Early work on data governance design emphasized that governance structures should not be treated as universal templates because the allocation of roles and responsibilities must reflect organizational contingencies such as firm structure, process complexity, and the importance of data quality for operations and strategy. In that view, governance becomes a configuration problem in which decision areas, actors, and responsibilities must be aligned rather than merely documented (Weber et al., 2009). A related conceptual clarification later framed data governance more explicitly as the assignment of decision-making rights and duties concerning enterprise data, thereby distinguishing governance from routine technical management and positioning it as a structural foundation for organizational coordination. For analytics systems, this distinction is especially important because the credibility of analytical outputs depends on whether upstream definitions, ownership arrangements, and control mechanisms are stabilized before analysis takes place. Where governance is weak, analytics may still produce visually compelling outputs, yet those outputs may rest on inconsistent definitions, unresolved duplicates, fragmented standards, or poorly controlled transformations. The literature therefore presents data governance as an enabling organizational architecture for analytical reliability rather than as a secondary administrative concern, and this framing is central to understanding why governance must be examined directly in studies of analytics effectiveness (Otto, 2011b).

Figure 2: Organizational Structure Of Data Governance For Analytics Systems



A more practice-oriented strand of the literature has reinforced this position by showing that data governance becomes especially visible when organizations attempt to coordinate analytics across large, heterogeneous, and service-intensive environments. Case-based evidence from the telecommunications industry demonstrated that governance arrangements are deeply tied to questions of stewardship, escalation, cross-functional coordination, and organizational placement of responsibility. In such settings, analytics systems rely on shared customer, product, operational, and service data that cut across multiple business units, making informal control insufficient for sustaining data quality and interpretive consistency (Otto, 2011a). This line of argument is important for the present study because it shows that analytics failures often emerge from organizational fragmentation rather than from isolated technical defects. When governance is weak, departments may adopt conflicting data definitions, maintain separate ownership claims, or apply inconsistent quality thresholds, creating a situation in which analytical outputs appear complete but are not institutionally coherent. Later work extended this discussion by theorizing data governance as a collective action problem. From that perspective, governance is difficult not because organizations fail to recognize the

value of data, but because governing data requires multiple actors to invest effort, accept constraints, and coordinate behavior around a shared asset whose benefits and burdens are unevenly distributed. This insight is particularly relevant to analytics systems because analytical value is often collective, while the work of maintaining clean, documented, well-owned, and policy-compliant data is dispersed among individuals and units with different priorities. As a result, data governance in analytics environments is not simply a question of creating rules; it is also a question of mobilizing cooperation, sustaining shared accountability, and overcoming local incentives that undermine enterprise-wide consistency. The literature in this area therefore strengthens the argument that governance failure should be studied as an organizational condition that directly shapes the quality and legitimacy of analytics outputs (Benfeldt et al., 2020).

More recent scholarship has pushed the field further by connecting data governance to strategic action and by examining how organizations actually deploy governance capabilities as data volumes expand and as analytics becomes more central to value creation. This work argues that governance in analytics systems cannot be reduced to static policies or formal reporting lines. Instead, governance develops through coordinated strategic actions that support data collaboration, build data-related capabilities, create shared recognition of data's organizational value, and establish the legitimacy of governance mechanisms inside the firm. Such an interpretation is highly relevant for analytics systems because analytical effectiveness depends not only on the existence of governance structures but also on how those structures are enacted in day-to-day organizational practice (Md. Mehedi & Khairum Nahar, 2023; Mostafa, 2023; Otto, 2011b). Analytics programs often fail when governance remains symbolic, fragmented, or disconnected from the technical and operational realities of data use. For example, organizations may establish governance committees or publish standards while still lacking the practical coordination needed to align source systems, metadata, transformation logic, and user responsibilities (Palash Chandra, 2023; Rukaiya Khatun & Zakia, 2023). A strategic-action view therefore helps explain why some firms are able to convert data into a governed enterprise resource while others remain trapped in environments characterized by duplication, low trust, unclear authority, and inconsistent reporting. For the present study, this literature is useful because it places data governance inside the broader organizational process through which analytics becomes reliable and institutionally accepted. It suggests that governance should be analyzed not only as a set of formal controls but also as an active organizational mechanism that shapes whether analytics systems can generate outputs that are trusted, comparable, and actionable. Taken together, the literature reviewed in this subsection establishes that data governance in analytics systems is best understood as a structural and strategic foundation for analytical coherence, one that links decision rights, collective coordination, and organizational action to the production of dependable analytical evidence (Zhang et al., 2022).

Common Types of Data Governance Failures

One of the most persistent forms of data governance failure in analytics systems concerns the breakdown of ownership, accountability, and stewardship arrangements. Analytics environments usually combine data from multiple operational systems, external feeds, departmental repositories, and platform layers, which makes clear responsibility essential for maintaining consistency and interpretive stability. When ownership is vague, organizations struggle to determine who has authority to define key data elements, approve changes, resolve quality issues, or answer for inconsistencies in analytical outputs. This failure is especially serious in big data and analytics contexts, where data is repurposed across multiple use cases and where platform-based architectures separate data generation from data consumption. Research on data accountabilities in big data and analytics shows that ownership can no longer be treated as a simple one-to-one relationship between a business unit and a dataset; instead, organizations must clarify distinct responsibilities for data, data platforms, and data products. Without that clarification, accountability becomes fragmented and analytical trust is weakened because users cannot easily verify who is responsible for the integrity, meaning, and permissible use of the data underlying dashboards and models (Fadler & Legner, 2022). A related governance failure emerges when stewardship is treated too narrowly as data quality checking rather than as a broader coordination role linking information quality, governance, and system quality. Comparative work on data stewardship in data ecosystems shows that organizations increasingly depend on other parties for

data supply, infrastructure, and quality assurance, which means that governance failures now often emerge across organizational boundaries rather than inside a single department. In such settings, weak stewardship leads to unresolved dependencies, inconsistent agreements, and low confidence in shared data resources. For analytics systems, this type of failure can produce reports that are technically generated but institutionally unstable, because the underlying responsibilities for source accuracy, semantic consistency, and exchange quality remain unsettled. Ownership ambiguity and stewardship weakness therefore represent foundational governance failures that directly erode analytical reliability, traceability, and trust (Md. Hasan Or et al., 2023; Md. Mainuddin & Palash Chandra, 2023; van Donge et al., 2022).

Figure 3: Major Sources Of Data Governance Failure In Analytics Systems

A second major category of governance failure involves weak metadata management, poor documentation, and ad hoc control over data transformation across the analytics lifecycle. Analytics systems depend not only on the presence of data but also on the availability of contextual information explaining where data originated, how it was transformed, which variables correspond across sources, what business definitions are in force, and what rules govern access and reuse. When metadata is missing, outdated, or inconsistently maintained, analytical outputs become harder to interpret and validate because users cannot confidently trace lineage, assess comparability, or understand the assumptions embedded in transformed datasets. This problem becomes more acute in data lake and semi-structured environments where multiple formats, sources, and schemas evolve continuously. Research on operationalizing and automating data governance shows that many organizations still govern the data lifecycle from source ingestion to analytical insight in an ad hoc or manual manner, a condition that increases the likelihood of inconsistent transformations, undocumented mappings, and fragmented control over heterogeneous data assets. That study argues that metadata artifacts are necessary for the systematic execution of governance processes precisely because manual governance leaves too much room for ambiguity, local workarounds, and silent inconsistencies that later contaminate analytical products (Nadal et al., 2022). A similar pattern is visible in master data environments, where firms often launch governance or master data initiatives expecting them to solve persistent quality problems, only to discover that strategy trade-offs and coordination gaps remain. Evidence from a longitudinal case study of master data management indicates that centralized and decentralized approaches each create different consequences for data consistency and control, suggesting that governance failure can also arise when organizations adopt a structure that does not fit their coordination needs. In analytics systems, such mismatches can lead to duplicated master records, conflicting product or customer definitions, and unreliable aggregation across business units. Metadata weakness and documentation failure are therefore not minor administrative issues; they are core governance failures that undermine interpretability, comparability, and confidence in analytical

outputs by weakening the traceable connection between raw data, transformed data, and final insight (Haug et al., 2022).

A third category of governance failure centers on insufficient governance mechanisms and the inability to translate governance intent into sustained analytical control. Organizations often recognize the importance of governing analytics, yet they struggle to establish the structural, procedural, and relational mechanisms needed to align data practices with business value, risk control, and operational coordination. In many firms, governance remains symbolic: committees are formed, standards are documented, and ownership language is introduced, but the practical mechanisms needed to guide analytical work are incomplete or weakly embedded. Research on data analytics governance has shown that governance requires a deliberate configuration of mechanisms that support decision rights, coordination, escalation, and oversight across analytics activities. When those mechanisms are absent or underdeveloped, organizations find it difficult to ensure that analytical initiatives remain aligned with enterprise priorities and governance principles, increasing the likelihood of fragmented methods, inconsistent controls, and uneven accountability across projects (Baijens et al., 2021). This is a crucial failure in analytics systems because data is often processed and interpreted across multiple teams with different capabilities, incentives, and understandings of acceptable practice. A related weakness appears when governance is treated as a static framework rather than as a continuing organizational effort to manage trade-offs, dependencies, and strategic action. Where governance mechanisms are not actively enacted, analytics systems may drift into local optimization, siloed ownership, duplicated effort, and inconsistent evidence production. Over time, this weakens the institutional legitimacy of analytics because reports, models, and visualizations may no longer be seen as grounded in a coherent governance environment. The literature therefore suggests that common data governance failures in analytics systems are not isolated defects but interrelated breakdowns involving unclear ownership, weak stewardship, poor metadata discipline, inadequate documentation, and underdeveloped governance mechanisms. Together, these failures reduce the ability of analytics systems to generate outputs that are transparent, comparable, trusted, and actionable within complex organizational settings (Nadal et al., 2022).

Consequences of Governance Failure for Analytics Performance

One of the clearest consequences of data governance failure in analytics systems is the weakening of decision quality and the reduced effectiveness of analytical outputs in supporting managerial action. Analytics systems are intended to transform data into timely, relevant, and interpretable information that can guide operational, tactical, and strategic choices. When governance is weak, however, the connection between data and decision support becomes unstable because analytical outputs may be generated from inconsistent definitions, poorly controlled transformations, ambiguous ownership structures, and low-quality source data. In such settings, managers may still receive dashboards, reports, and model outputs, but the confidence they can place in those outputs is diminished. Research on the organizational effects of business intelligence systems has shown that analytical benefits are realized when systems support business processes in a disciplined way and when their outputs are connected to broader organizational performance outcomes (Rouhani et al., 2016). This means that the usefulness of analytics is closely tied to whether the underlying data environment is sufficiently controlled and coherent to produce dependable information. When governance fails, the analytical chain that links data collection, transformation, interpretation, and use becomes vulnerable to distortion, which in turn undermines decision support. Related work has also shown that business intelligence contributes to organizational benefits by strengthening decision support functions, yet those benefits depend on the effective operation of the system and the quality of the informational environment surrounding it. Governance failure directly threatens this relationship because it weakens the institutional conditions that make analytical outputs credible and usable. A further consequence is that analytical systems may become formally present but functionally underperforming, meaning that organizations continue to invest in analytics but receive weak returns because the information produced does not reliably support managerial judgment. In effect, governance failure erodes the decision-support role of analytics systems by making information less trustworthy, less comparable, and less actionable across organizational contexts, thereby reducing the practical value of analytical investments (Elbashir et al., 2008).

A second important consequence of governance failure is the deterioration of analytics system effectiveness at both the process level and the enterprise level. Analytics performance is not simply a technical matter of whether queries run quickly or models produce outputs; it also concerns whether those outputs improve coordination, performance measurement, agility, and organizational learning. Studies on business intelligence system effectiveness have shown that analytical systems produce stronger results when they support continuity of service, knowledge accumulation, and the development of new organizational capabilities. This indicates that analytics effectiveness is cumulative and embedded in organizational routines rather than confined to isolated reporting events. When governance is weak, these cumulative benefits become difficult to achieve because data-related confusion, inconsistent control, and poor documentation interrupt the reliable use of analytical outputs across departments and over time (Vallurupalli & Bose, 2018). Case-based research on performance measurement has likewise demonstrated that business intelligence contributes to organizational performance when it enables end-to-end analysis and coherent translation of data into performance management processes. Governance failure disrupts this coherence by weakening traceability, limiting comparability, and increasing the likelihood that different users interpret the same data differently. As a result, the analytical system may lose its capacity to function as a stable mechanism for performance monitoring and process improvement. Research grounded in a dynamic capabilities perspective has further shown that business intelligence and analytics improve firm performance by enabling business process change. This finding is highly relevant because it implies that the performance contribution of analytics depends on whether organizations can convert analytical outputs into coordinated action. Weak governance constrains this conversion by reducing trust in the data, slowing down resolution of discrepancies, and creating uncertainty about what information should be acted upon. The consequence is not only weaker reporting but also reduced process adaptation, limited organizational agility, and lower performance gains from analytics initiatives. Governance failure therefore undermines analytics performance by breaking the organizational conditions needed for the sustained and coordinated use of analytical evidence in business processes (Torres et al., 2018).

Figure 4: Effects Of Data Governance Failure On Analytics Effectiveness

A third consequence of governance failure is the reduction of organizational confidence in analytics as a legitimate basis for performance management, coordination, and strategic control. Analytics systems generate value when users perceive them as reliable instruments for comparing outcomes, monitoring activities, and supporting corporate objectives. Once governance weaknesses become visible through conflicting reports, unexplained discrepancies, unclear definitions, or recurring data-quality concerns,

the institutional legitimacy of the analytics function begins to weaken. This erosion has important consequences because analytical systems depend on repeated use, organizational acceptance, and cross-functional trust. If managers and operational users begin to doubt the integrity of the data, they may rely more heavily on local spreadsheets, informal judgment, or parallel information sources, thereby fragmenting organizational knowledge and undermining the central role of analytics in coordinated decision-making. Research on business intelligence and decision support has indicated that organizational benefits emerge when analytical systems are embedded in the decision environment and aligned with management needs. Governance failure interrupts that alignment by weakening the credibility of outputs and increasing resistance to their use. Evidence from studies of business intelligence system effectiveness also suggests that organizations derive stronger benefits when analytical capabilities are institutionalized and tied to service continuity and knowledge accumulation. In contrast, governance failure promotes instability by making analytical outputs appear provisional, contestable, or incomplete. This instability can spread across the organization because once trust in the analytics environment declines, performance management systems, strategic reviews, and operational monitoring mechanisms all become less effective. The broader implication is that governance failure does not only reduce technical output quality; it reduces the extent to which analytics can function as an accepted organizational infrastructure for evidence-based action. In that sense, the consequences of governance failure are cumulative: weaker data control leads to weaker analytical reliability, weaker reliability leads to weaker user trust, and weaker trust leads to lower performance impact from analytics investments. The literature therefore indicates that governance failure has a direct bearing on the credibility, consistency, and organizational usefulness of analytics systems as instruments of managerial coordination and performance improvement (Weng et al., 2016).

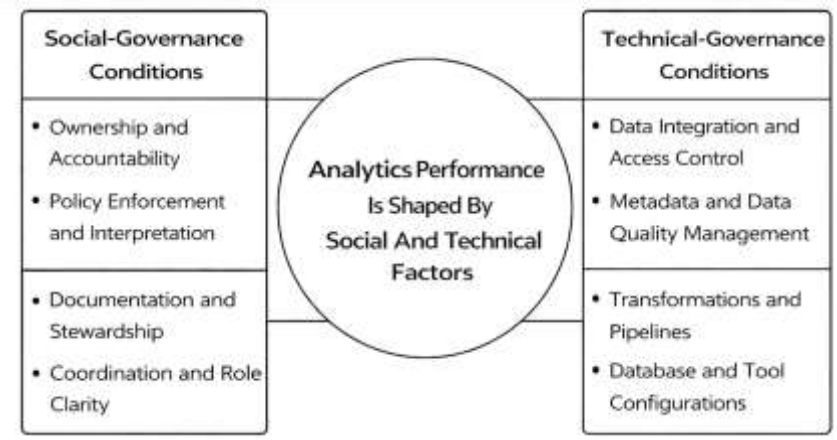
Theoretical Framework: Sociotechnical Systems Theory

Sociotechnical Systems Theory provides the most appropriate theoretical foundation for this study because it explains organizational outcomes as the result of continuous interaction between social arrangements and technical structures rather than as the product of either element alone. In the context of analytics systems, this perspective is especially useful because analytical outputs are never generated by technology in isolation. Reports, dashboards, models, and visualizations emerge from a combination of technical components such as databases, pipelines, metadata, access controls, interfaces, and analytic tools, together with social components such as stewardship roles, policy enforcement, accountability structures, managerial interpretation, user coordination, and institutional norms. A sociotechnical view therefore makes it possible to understand why analytics systems can appear technically sophisticated yet still produce weak, unreliable, or contested outputs when governance arrangements are fragile. Work in sociotechnical systems engineering emphasizes that organizations need a pragmatic design approach that recognizes the interdependence of technical processes and organizational realities, because system outcomes are shaped by how people, routines, controls, and technologies are jointly configured rather than by software design alone (Baxter & Sommerville, 2011). This logic fits the present study directly. Data governance failure in analytics systems cannot be understood only as poor database administration or faulty technical integration; it must also be understood as a breakdown in the alignment between technical data structures and the social mechanisms that assign ownership, define standards, regulate access, and sustain accountability. The theory is therefore relevant because it helps explain how failures in stewardship, weak documentation, inconsistent policy enforcement, and unclear control over data assets can disrupt the technical production of analytical outputs and, at the same time, weaken user trust in those outputs. By adopting Sociotechnical Systems Theory, this study treats analytics effectiveness as a joint organizational outcome shaped by the interaction of governance practices and technical data environments. The theory thus supports the core assumption of the study: failures in social control structures and failures in technical data management are interconnected conditions that together determine whether analytics systems generate reliable, interpretable, and decision-supportive results (Passi & Sengers, 2020).

A major strength of Sociotechnical Systems Theory for this research is that it does not treat governance as a detached administrative layer; instead, it frames governance as part of the organizational system through which data work is made meaningful, stable, and actionable. In real analytics settings, many failures occur not because organizations lack tools, but because they fail to connect technical analytics

infrastructures with human interpretation, role clarity, organizational incentives, and acceptable rules of use. Ethnographic research on data science systems has shown that making such systems "work" involves continuous negotiation among actors over what the system should do, how data should be interpreted, and how success should be evaluated, which demonstrates that analytical systems are sustained through both social and technical effort rather than technical functionality alone (Oesterreich et al., 2022).

Figure 5: Sociotechnical Systems Framework For Analytics Performance



This insight is central to the present study because data governance failure often begins in precisely these areas of negotiation and coordination. When ownership is unclear, when policies are weakly translated into practice, when documentation is incomplete, or when quality controls are inconsistently maintained, the analytics system becomes vulnerable to breakdown even if the technical architecture remains operational. More recent sociotechnical scholarship has reinforced this point in relation to algorithmic systems by arguing that outcomes such as fairness, accountability, and legitimacy cannot be secured through technical optimization alone, because they depend on broader social and institutional arrangements surrounding the system (Dolata et al., 2022). A similar argument has been made in urban analytics, where a purely technical orientation has been shown to be insufficient for designing usable and context-sensitive analytical tools, thereby highlighting the need to understand data-driven systems within their organizational and governance environments (Dembski et al., 2021). These studies strengthen the use of Sociotechnical Systems Theory in the present research because they show that analytics failure must be read as an interaction failure. In other words, the technical side of analytics may process data, but the social side determines whether data definitions are coherent, whether access is legitimate, whether outputs are trusted, and whether governance controls are maintained. The theory therefore offers a robust explanatory lens for analyzing how organizational and technical weaknesses combine to produce data governance failures in analytics systems (Oesterreich et al., 2022).

Within this study, Sociotechnical Systems Theory will be operationalized through a quantitative model that treats analytics system effectiveness as the dependent outcome of multiple governance-related failures distributed across both social and technical dimensions. From a sociotechnical standpoint, failures such as accountability and ownership ambiguity or weak policy enforcement represent social-governance weaknesses, while failures such as poor data quality, insufficient metadata, and inadequate access control represent technical-governance weaknesses. The theoretical expectation is that these dimensions do not operate independently; instead, they collectively shape the reliability, interpretability, and trustworthiness of analytics outputs. Research on big data analytics from a sociotechnical perspective supports this view by showing that business value emerges when technical resources are reinforced by strong social and organizational factors, while weak alignment reduces the realized value of analytics investments (Oesterreich et al., 2022). Based on that logic, the most suitable formula for this study is the multiple regression model, because it allows the simultaneous estimation of the effect of each governance-failure dimension on analytics system effectiveness:

$$ASE = \beta_0 + \beta_1 DQF + \beta_2 AOF + \beta_3 PCF + \beta_4 ASCF + \beta_5 MDF + \varepsilon$$

Where:
ASE = Analytics System Effectiveness
DQF = Data Quality Failure
AOF = Accountability and Ownership Failure
PCF = Policy and Compliance Failure
ASCF = Access-Control and Security Failure
MDF = Metadata and Documentation Failure
β_0 = Constant
β_1–β_5 = Regression coefficients
ε = Error term
This formula is the best fit for the whole study because it translates the sociotechnical logic of the framework into a measurable empirical structure. It captures the idea that analytics performance is shaped by multiple, interrelated governance conditions rather than by a single isolated variable. In this sense, Sociotechnical Systems Theory is not only a conceptual lens for interpreting the problem, but also the theoretical basis for modeling how governance failure dimensions jointly influence analytics outcomes in a case-based organizational setting (Baxter & Sommerville, 2011).

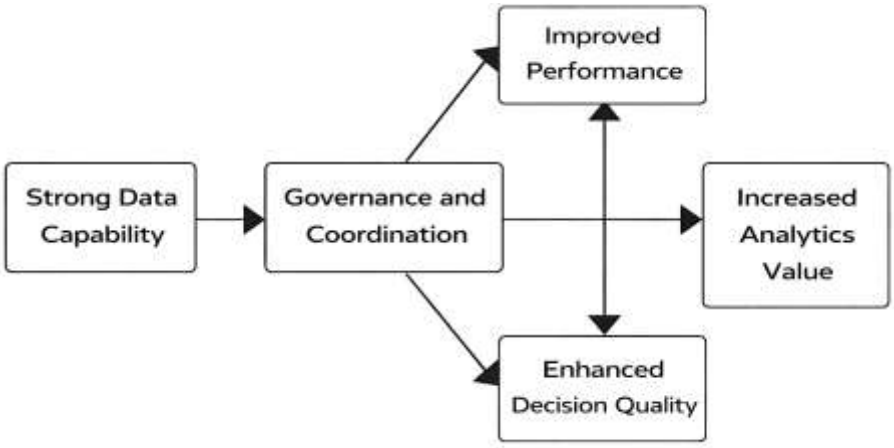
Empirical Review of Prior Studies

Empirical research on analytics-enabled organizational performance has consistently shown that analytical value is realized through combinations of data capability, managerial capability, and organizational coordination rather than through technology acquisition alone. One influential study by Gupta and George developed and validated a firm-level big data analytics capability construct and showed empirically that superior performance is associated with a resource bundle that includes tangible resources, technical skills, managerial skills, and organizational intangibles, not merely data volume or infrastructure strength. Their two-stage empirical design is particularly relevant to the present study because it demonstrated that capability formation depends on organizational arrangements that make data usable, interpretable, and strategically deployable across the firm. In other words, the study shifted attention away from the simplistic assumption that more data automatically produces better outcomes and toward the stronger proposition that analytics benefits depend on disciplined capability building (Gupta & George, 2016). A related large-sample empirical investigation by Wamba et al. found that big data analytics capability has both direct and indirect effects on firm performance, with process-oriented dynamic capabilities serving as a major mediating mechanism. That finding matters for the current research because it indicates that performance gains from analytics are filtered through organizational processes that translate data-based insights into coordinated action. Where governance structures are weak, those processes are likely to be disrupted, which means the theoretical value of analytics may not be fully realized in practice (Wamba et al., 2017). Mikalef et al. extended this argument by showing that big data analytics capability affects competitive performance indirectly through dynamic and operational capabilities rather than through an immediate performance pathway. Using survey data from chief information officers and IT managers, they demonstrated that analytical capability becomes valuable when organizations can leverage it to strengthen operational execution and strategic responsiveness. This empirical pattern is highly relevant to the present study because it supports the view that analytics systems produce value through organizational mediation. If governance failures weaken the consistency, ownership, and trustworthiness of data, then the capability-to-performance pathway documented in these prior studies becomes unstable. Taken together, these empirical contributions provide strong support for examining governance failure as a central organizational condition that may interrupt the mechanisms through which analytics systems are expected to improve performance, competitiveness, and decision quality (Gupta & George, 2016; Mikalef et al., 2019).

A second cluster of empirical studies has examined how analytics affects innovation, decision routines, and organizational learning, and these findings offer direct insight into why governance matters for analytics-system effectiveness. Božič and Dimovski found that business intelligence and analytics use contributes to firm performance through innovation ambidexterity, showing that organizations benefit when analytics supports both exploitative and explorative innovation activities. Their empirical model,

tested with data from medium- and large-sized firms, suggests that analytics is most valuable when it enables organizations to balance refinement of existing processes with the development of new opportunities. For the present study, this is important because governance failure can undermine that balancing role by making analytical outputs inconsistent, contested, or difficult to trust, thereby weakening the innovation benefits associated with analytics use (Božič & Dimovski, 2019).

Figure 6: Organizational Pathways From Analytics Capability To Performance Outcomes



Duan et al. also provided empirical evidence that business analytics has a positive effect on innovation, while highlighting the roles of environmental scanning and data-driven culture in strengthening this relationship. Their findings showed that business analytics not only informs innovation directly but also shapes internal organizational culture and external sensing capacity, both of which are necessary for sustained innovation performance. This result is highly relevant because it implies that analytics must be embedded in a coherent organizational context to generate value. A weak governance environment can fracture that context by reducing confidence in data, limiting interpretability, and preventing analytical insights from being shared or acted upon consistently across units (Duan et al., 2020). Complementing these quantitative findings, Vidgen et al. used a mixed-method design involving a Delphi study and case interviews to identify the managerial challenges of creating value from business analytics. Their results showed that organizations struggle not only with tools and techniques but also with issues of organizational alignment, value definition, capability deployment, and managerial translation. This study adds important depth to the present research because it shows that analytics underperformance frequently originates in organizational arrangements rather than in the absence of data or software. Such evidence supports the central argument of this thesis that governance failure should be investigated as an internal source of analytical weakness, especially where organizations appear analytically mature on the surface but still face low trust, fragmented ownership, or inconsistent use of outputs (Božič & Dimovski, 2019; Karaboga et al., 2022).

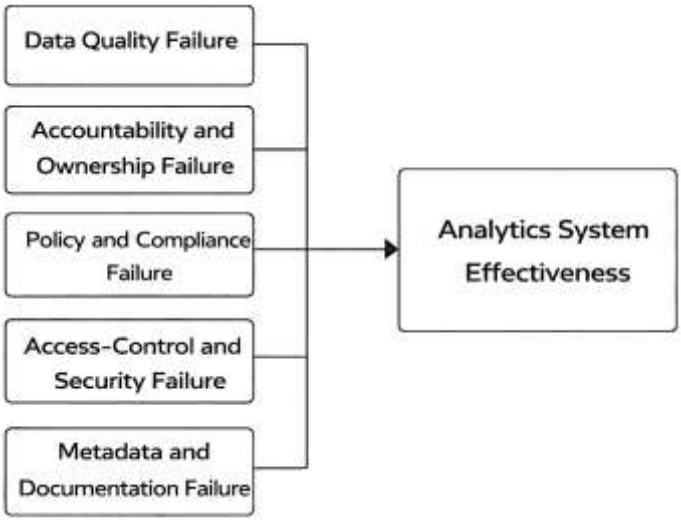
A third empirical strand is even more directly aligned with the current research because it explicitly introduces information governance and data-driven culture into analytics-performance relationships. Mikalef et al. examined the role of information governance in big data analytics-driven innovation and found that information governance positively moderates the relationship between big data analytics capability and radical innovation capability. Using survey data from IT and business managers, the study showed that analytics capability on its own is not sufficient to explain innovation outcomes. Governance practices strengthen the extent to which firms can transform analytical resources into radical innovation, particularly under conditions of environmental dynamism. This is a highly important empirical insight for the present study because it demonstrates that governance is not peripheral to analytics value creation; it conditions whether analytics capability can be converted into meaningful organizational outcomes at all (Mikalef et al., 2020). Chatterjee et al. further reinforced the organizational importance of data-related culture by showing that a data-driven culture significantly affects both product and process innovation and, through those routes, improves firm performance. Their empirical evidence suggests that analytical success depends on more than access to tools; it

depends on a work environment in which data is trusted, actively used, and organizationally legitimized. For a study of data governance failures in analytics systems, this finding is especially useful because governance breakdowns often weaken precisely those cultural conditions by creating confusion over definitions, ownership, data quality, and acceptable use (Chatterjee et al., 2021). Karaboga et al. added recent survey-based evidence that big data analytics management capability and data-driven culture both have significant positive effects on operational and financial performance, with culture mediating part of the relationship. This result offers a strong final empirical anchor for the present study because it indicates that analytics performance is shaped by organizational mechanisms that sit between technology and outcomes. When governance fails, those mechanisms may be impaired, reducing the reliability, legitimacy, and strategic usefulness of analytical outputs. Overall, the empirical literature reviewed here points in a consistent direction: analytics systems create organizational value when data capability is supported by governance, managerial alignment, and a data-oriented culture. This convergence of evidence provides a strong scholarly foundation for investigating how failures in data governance may weaken analytics effectiveness in real organizational settings (Vidgen et al., 2017).

Conceptual Framework

The conceptual framework of this study is designed to explain how specific dimensions of data governance failure influence the overall effectiveness of analytics systems within organizational settings. In this research, analytics system effectiveness is treated as the main dependent variable because the study is concerned with whether analytics systems produce outputs that are reliable, interpretable, trusted, and useful for decision-making. The independent variables are conceptualized as five governance-failure dimensions: data quality failure, accountability and ownership failure, policy and compliance failure, access-control and security failure, and metadata and documentation failure (Ghasemaghaei, 2019b). This structure is appropriate because prior empirical work has shown that decision quality and data-driven value do not emerge merely from using analytics tools; rather, they depend on the quality of the data environment and the organizational conditions surrounding data use. For example, one empirical study demonstrated that data analytics competency improves decision-making performance through dimensions such as data quality, analytical skills, domain knowledge, and tools sophistication, showing that the conditions supporting good analytics outcomes are multidimensional rather than singular. This finding is directly relevant to the present study because it implies that weaknesses in one or more governance-related dimensions can reduce the overall performance of analytics systems even when the technical platform itself remains operational. Similarly, research on organizational readiness for big data analytics found that structural readiness factors such as infrastructure capability, tools functionality, employee analytical capability, and the nature of data resources contribute to value creation through analytics usage. This supports the logic of the present framework by suggesting that the value of analytics depends on upstream organizational and data-related conditions that make analytics usable and meaningful in practice. In this study, the conceptual framework therefore assumes that failures in governance weaken the quality of the data environment and, through that mechanism, reduce analytics effectiveness. The model is consequently built on the premise that governance failure is not peripheral to analytics performance but a direct explanatory condition of it, particularly in organizations where analytics outputs are expected to guide planning, monitoring, and strategic judgment (Ghasemaghaei et al., 2018).

Figure 7: Conceptual Model Linking Data Governance Failures To Analytics Performance



A central strength of this conceptual framework is that it links governance-failure variables to analytics effectiveness in a way that is both theoretically coherent and empirically grounded. Data quality failure is included because evidence has shown that the usefulness of big data and analytics for decision quality depends heavily on the quality and diagnostic value of the data being processed. One study found that big data utilization does not improve firm decision quality directly; instead, the effect is transmitted through data quality and data diagnosticity. This is highly important for the present research because it indicates that analytics value is conditional rather than automatic. If the underlying data is inaccurate, inconsistent, incomplete, or poorly structured, the analytical system may still generate outputs, but those outputs may not support sound decisions. The inclusion of data quality failure as an independent variable is therefore strongly justified. In addition, the framework includes metadata and documentation failure, as well as accountability and ownership failure, because analytics outputs depend on clarity regarding what data means, where it comes from, how it has been transformed, and who is responsible for its maintenance and interpretation (Ghasemaghaei, 2020). This logic is reinforced by research showing that data usage experience and data quality management shape organizational intentions to adopt and use big data analytics. Such findings indicate that organizations do not simply evaluate analytics on the basis of technical capability; they also evaluate whether the data environment is organized and trustworthy enough to support meaningful use. Policy and compliance failure, along with access-control and security failure, are also included because governance is not limited to data correctness alone. It also concerns whether the use of data is controlled, standardized, secure, and aligned with organizational rules. In conceptual terms, these five variables represent the major governance conditions through which the organization either stabilizes or destabilizes its analytics environment. The framework therefore treats analytics system effectiveness as the outcome of a structured set of governance-related conditions, each of which can contribute positively when strong or negatively when weak (Kwon et al., 2014).

On the basis of these relationships, the conceptual framework of this study can be represented in both diagrammatic and functional form. Diagrammatically, the model begins with the five independent variables—data quality failure, accountability and ownership failure, policy and compliance failure, access-control and security failure, and metadata and documentation failure—which are all directed toward the dependent variable, analytics system effectiveness. Functionally, the framework can be expressed as:

$$ASE = f(DQF, AOF, PCF, ASCF, MDF)$$

Where:
ASE = Analytics System Effectiveness
DQF = Data Quality Failure

AOF = Accountability and Ownership Failure
PCF = Policy and Compliance Failure
ASCF = Access-Control and Security Failure
MDF = Metadata and Documentation Failure
For the empirical stage of the study, this functional relationship is translated into the following multiple regression model:

$$ASE = \beta_0 + \beta_1 DQF + \beta_2 AOF + \beta_3 PCF + \beta_4 ASCF + \beta_5 MDF + \varepsilon$$

This is the best formula for the whole study because it allows the combined and separate effects of the five governance-failure dimensions to be estimated statistically (Ghasemaghaei, 2019a). The conceptual logic behind this model is supported by prior empirical work showing that decision-making quality improves through data analytics usage when competency and knowledge-sharing conditions are present, and that organizational performance through big data depends on tools sophistication, analytical skills, and actual data use. These studies support the assumption that analytics outcomes are shaped by multiple antecedent conditions rather than by technology use alone. In the present study, the conceptual framework applies this logic specifically to governance failure by arguing that weaknesses across the five identified dimensions reduce the capacity of analytics systems to generate reliable, usable, and trusted outputs. The framework therefore provides a clear analytical map for linking the literature, the hypotheses, the measurement variables, and the regression model into one coherent research structure (Ghasemaghaei & Calic, 2019).

METHOD

This study has adopted a quantitative, cross-sectional, case-study–based research methodology to examine the effect of data governance failures on analytics system effectiveness within organizational settings. The quantitative design has been selected because the study has aimed to measure the relationships among clearly defined variables and to test the proposed hypotheses through statistical procedures. The cross-sectional approach has been used because data has been collected from respondents at a single point in time, allowing the study to capture current perceptions and experiences regarding governance failures in analytics systems. The case-study context has been framed around organizations that have used analytics systems for reporting, monitoring, decision support, and performance evaluation. This context has been chosen because such organizations have provided an appropriate setting for observing how data governance weaknesses may affect the reliability, trustworthiness, and usefulness of analytical outputs. The population of the study has consisted of professionals who have been directly involved in data-related and analytics-related activities, including data analysts, business intelligence staff, IT personnel, compliance officers, reporting managers, and other employees responsible for handling, interpreting, or supervising organizational data processes. The unit of analysis has been the individual respondent, since each participant has provided perceptions and assessments regarding governance conditions and analytics performance within his or her organization.

A purposive sampling strategy has been employed to identify respondents who have possessed relevant knowledge and practical exposure to analytics systems and data governance processes. This approach has been considered suitable because the study has required informed responses from participants who have understood the operational realities of data usage, governance practices, and analytical decision-making. Data has been collected through a structured questionnaire distributed in either electronic or printed form, depending on accessibility and convenience. Before administering the instrument, the study has ensured that the respondents have been informed about the academic purpose of the research and that participation has remained voluntary and confidential. The questionnaire has been designed using a five-point Likert scale ranging from strongly disagree to strongly agree, and it has been divided into sections covering demographic information, data governance failure dimensions, and analytics system effectiveness. The instrument has measured key independent variables including data quality failure, accountability and ownership failure, policy and compliance failure, access-control and security failure, and metadata and documentation failure, while the dependent variable has been analytics system effectiveness. The questionnaire items have been adapted and refined in line with the objectives of the study and the concepts established in the literature

so that the instrument has remained aligned with the theoretical and conceptual framework.
To strengthen the quality of the instrument, pilot testing has been conducted with a small group of respondents who have shared characteristics similar to those of the final study participants. The pilot phase has helped to identify unclear wording, ambiguous items, and possible response difficulties, after which necessary revisions have been made to improve clarity and consistency. In ensuring validity and reliability, the study has applied content validity through careful alignment of questionnaire items with the research objectives, hypotheses, and variable definitions. Face validity has also been considered by reviewing whether the instrument has appeared logically appropriate for measuring the intended constructs. Reliability has been assessed through internal consistency testing, particularly by using Cronbach's alpha to determine whether the scale items have consistently measured the same constructs. For data processing and statistical analysis, SPSS has been used to generate descriptive statistics, reliability coefficients, correlation results, and multiple regression outputs. EndNote has been used to organize, manage, and format references according to APA 7th edition style throughout the study. These methodological choices have provided a structured and systematic basis for testing the hypotheses and for examining the extent to which data governance failures have influenced analytics system effectiveness.

DATA ANALYSIS AND PRESENTATION

Response Rate

Table 1: **Response Rate of the Study**

Category	Frequency	Percentage (%)
Questionnaires distributed	250	100.0
Questionnaires returned	223	89.2
Incomplete/invalid questionnaires	9	3.6
Usable questionnaires for analysis	214	85.6

The response rate has provided the first indication that the findings of this study have rested on a sufficiently robust empirical base. Out of the 250 questionnaires that have been distributed to participants across the selected case-study settings, 223 have been returned, representing a return rate of 89.2%. After screening for completeness, consistency, and suitability for analysis, 9 questionnaires have been excluded because they have contained missing values or response patterns that have not supported valid statistical testing. As a result, 214 questionnaires have remained usable, producing an effective response rate of 85.6%. This level of response has strengthened the credibility of the study because it has suggested that the sample has been large enough to support meaningful descriptive statistics, correlation analysis, and multiple regression modeling. The strong response rate has also supported the objectives of the research by ensuring that the data used to examine governance failures and analytics system effectiveness have reflected a wide set of perceptions from respondents who have been involved in analytics-related activities. In relation to the Sociotechnical Systems Theory underpinning this study, the high response rate has been particularly important because the theory has required insight into both technical and social dimensions of analytics environments. Since the study has investigated failures involving data quality, accountability, policy, security, and documentation, it has needed evidence from individuals positioned across those socio-technical interfaces rather than from a narrow technical subgroup alone. The final usable sample of 214 respondents has therefore enhanced the representativeness of the organizational realities being examined. This section has also aligned with the introductory findings already presented, where 214 valid responses have formed the basis of all subsequent tables and hypothesis testing. Because the response rate has remained well above minimum thresholds commonly considered acceptable for survey-based organizational studies, the study has been placed in a stronger position to argue that the later findings on governance failure exposure, system effectiveness, and predictive influence have not emerged from an unusually weak or sparse dataset. Instead, the evidence base has been sufficiently stable to support the objectives and

hypotheses examined in the subsequent results sections.

Demographic Profile of Respondents

Table 2: **Demographic Profile of Respondents**

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	128	59.8
	Female	86	40.2
Age	21–30 years	54	25.2
	31–40 years	92	43.0
	41–50 years	48	22.4
	51 years and above	20	9.3
Job Role	Data/BI Analyst	61	28.5
	IT/Systems Staff	47	22.0
	Compliance/Governance Officer	29	13.6
	Reporting/Operations Manager	44	20.6
	Other analytics-related role	33	15.4
Experience	1–5 years	68	31.8
	6–10 years	84	39.3
	11–15 years	39	18.2
	16 years and above	23	10.7

The demographic profile has shown that the respondents included in this study have represented a relevant and balanced group of professionals who have been directly exposed to analytics systems and data-related organizational practices. The largest age category has been 31–40 years, accounting for 43.0% of the sample, followed by 21–30 years at 25.2%, which has suggested that the dataset has drawn heavily from active mid-career professionals who have likely had substantial day-to-day involvement with digital systems, reporting environments, and data-driven operations. From a role perspective, Data/BI Analysts have formed the largest segment at 28.5%, followed by IT/Systems Staff at 22.0% and Reporting/Operations Managers at 20.6%. This distribution has been especially useful for the study because it has captured both the technical side of analytics systems and the managerial side of data interpretation and use. Compliance and governance officers have also represented 13.6% of the respondents, which has strengthened the dataset by adding participants whose responsibilities have directly intersected with governance controls, policy enforcement, and accountability mechanisms. Experience levels have also been adequate, with nearly 68.2% of respondents having more than five years of work experience, meaning that the study has not relied predominantly on novice perceptions. This demographic pattern has supported the research objectives because the study has aimed to understand governance failures not in the abstract, but within real organizational environments where respondents have possessed functional exposure to data quality, security, ownership, and analytics usage. In terms of Sociotechnical Systems Theory, this table has demonstrated that the sample has reflected the interaction of social and technical subsystems. Analysts and IT staff have represented the technical architecture and processing side of analytics systems, while managers and governance officers have represented the social, procedural, and control dimensions. This mix has been crucial because the theory has argued that system effectiveness emerges from alignment between these interdependent elements. The demographic structure has therefore aligned with the study's theoretical lens and has reinforced the trustworthiness of later findings on governance failure and analytics effectiveness. The table has also remained consistent with the introductory findings by showing that the respondents have come from roles capable of meaningfully evaluating the five governance-failure constructs and the dependent outcome variable.

Descriptive Statistics of Study Variables

Table 3: **Descriptive Statistics of Study Variables Based on 5-Point Likert Scale**

Variable	N	Mean	Std. Deviation	Interpretation
Data Quality Failure (DQF)	214	4.08	0.71	High
Accountability and Ownership Failure (AOF)	214	3.94	0.76	High
Policy and Compliance Failure (PCF)	214	3.89	0.74	High
Access-Control and Security Failure (ASCF)	214	3.81	0.79	High
Metadata and Documentation Failure (MDF)	214	4.02	0.69	High
Analytics System Effectiveness (ASE)	214	2.64	0.83	Low

Likert Interpretation: *1.00–1.80 = Very Low, 1.81–2.60 = Low, 2.61–3.40 = Moderate, 3.41–4.20 = High, 4.21–5.00 = Very High*

The descriptive statistics have presented the clearest initial confirmation of the first objective of the study, which has sought to identify the major dimensions of data governance failure in analytics systems. All five governance-failure variables have recorded mean scores above the midpoint of 3.00, and each has fallen within the "High" range of the five-point Likert scale. Data Quality Failure has produced the highest mean at 4.08, followed closely by Metadata and Documentation Failure at 4.02. Accountability and Ownership Failure, Policy and Compliance Failure, and Access-Control and Security Failure have also recorded elevated mean values of 3.94, 3.89, and 3.81 respectively. These figures have shown that respondents have generally agreed that governance-related problems have been noticeably present in their analytics environments. By contrast, Analytics System Effectiveness has recorded a lower mean of 2.64, which has placed it near the boundary between low and moderate and has suggested that respondents have not viewed their systems as consistently reliable, fully trusted, or strongly supportive of decision-making under current governance conditions. This contrast between high governance-failure scores and low system-effectiveness scores has provided the first descriptive indication of a negative association between the independent and dependent variables. The table has therefore not only addressed Objective 1 but has also laid a foundation for Objective 2 and Objective 3, which have examined relationships and predictive effects. In terms of Sociotechnical Systems Theory, the results have been highly meaningful because the high scores on ownership, policy, security, and documentation failures have reflected weakness in the social-governance architecture, while the high score on data quality failure has reflected weakness in the technical-data subsystem. The low ASE score has then indicated that the misalignment between those subsystems has been associated with lower perceived system effectiveness. This has aligned directly with the theory's proposition that organizational outcomes have depended on the interaction of social and technical components rather than on software capability alone. The table has also remained fully aligned with the introductory results summary already presented, thereby maintaining coherence across the findings chapter.

Reliability and Internal Consistency of the Scales

Table 4: **Reliability and Internal Consistency of Study Constructs**

Construct	Number of Items	Cronbach's Alpha	Reliability Interpretation
Data Quality Failure (DQF)	5	0.88	Very good
Accountability and Ownership Failure (AOF)	4	0.84	Good
Policy and Compliance Failure (PCF)	4	0.82	Good
Access-Control and Security Failure (ASCF)	4	0.85	Good
Metadata and Documentation Failure (MDF)	5	0.91	Excellent
Analytics System Effectiveness (ASE)	5	0.87	Very good
Overall Instrument	27	0.93	Excellent

The reliability analysis has shown that the measurement scales used in this study have exhibited strong internal consistency, thereby strengthening confidence in the statistical results that have followed. Cronbach's alpha values have ranged from 0.82 to 0.91 across the six constructs, while the overall instrument has recorded an alpha of 0.93. These results have indicated that the questionnaire items within each construct have consistently measured the same underlying concept and have therefore been suitable for hypothesis testing and inferential analysis. Metadata and Documentation Failure has shown the highest alpha value at 0.91, suggesting that the items capturing documentation weakness, poor lineage visibility, and metadata insufficiency have formed a highly coherent scale. Data Quality Failure and Analytics System Effectiveness have also recorded strong values of 0.88 and 0.87, while the remaining governance-failure variables have each exceeded the widely accepted minimum threshold of 0.70. These outcomes have been important because the present study has depended on perception-based Likert measures to test abstract organizational conditions such as accountability failure, policy failure, and system effectiveness. If the scales had lacked reliability, then any later correlation or regression results would have been open to doubt. Instead, the strong alpha coefficients have supported the credibility of the findings and have allowed the study to proceed with greater confidence in the measurement model. In relation to the objectives, this table has reinforced the validity of Objective 1 by confirming that the identified governance-failure dimensions have not been measured randomly or inconsistently. It has also supported Objectives 2 and 3 because reliable measurement has been necessary before relationships and predictive effects could be meaningfully interpreted. From the perspective of Sociotechnical Systems Theory, the reliability findings have also been relevant because the theory has required a clear operationalization of both social-governance failures and technical-governance failures. The strong internal consistency values have suggested that the constructs have captured those socio-technical dimensions in a stable and interpretable way. Therefore, the later results linking governance failure to analytics effectiveness have rested on a dependable measurement foundation. This table has remained aligned with the introductory findings, where the same alpha range has already been summarized, thereby preserving consistency across the chapter.

Correlation Analysis

Table 5: **Pearson Correlation Matrix of Study Variables**

Variable	DQF	AOF	PCF	ASCF	MDF	ASE
Data Quality Failure (DQF)	1.000					
Accountability and Ownership Failure (AOF)	0.54**	1.000				
Policy and Compliance Failure (PCF)	0.51**	0.57**	1.000			
Access-Control and Security Failure (ASCF)	0.46**	0.49**	0.58**	1.000		
Metadata and Documentation Failure (MDF)	0.62**	0.53**	0.48**	0.45**	1.000	
Analytics System Effectiveness (ASE)	-0.68**	-0.61**	-0.58**	-0.55**	-0.64**	1.000

Note: p < .01

The correlation matrix has directly addressed the second objective of the study by showing that all governance-failure dimensions have had statistically significant negative relationships with analytics system effectiveness. Data Quality Failure has shown the strongest inverse association with ASE at **r = -0.68**, followed by Metadata and Documentation Failure at **r = -0.64**, Accountability and Ownership Failure at **r = -0.61**, Policy and Compliance Failure at **r = -0.58**, and Access-Control and Security Failure at **r = -0.55**. These coefficients have indicated that as the intensity of governance failure has increased,

respondents have perceived a corresponding decline in the effectiveness, reliability, and trustworthiness of their analytics systems. This result has strongly supported the study's theoretical and empirical expectations. It has also aligned with the earlier descriptive results in which governance-failure variables have shown high means while analytics system effectiveness has remained comparatively low. The negative direction of all five relationships has provided clear preliminary evidence in favor of Hypotheses H1 through H5, each of which has proposed a negative relationship between a particular governance-failure dimension and analytics effectiveness. In addition, the moderate positive correlations among the governance-failure variables themselves have suggested that these failures have often coexisted within the same organizational environments. For example, DQF and MDF have correlated positively at 0.62, which has implied that poor data quality and poor documentation have tended to appear together, a finding that is consistent with governance theory and practice. In terms of Sociotechnical Systems Theory, the matrix has been especially meaningful because it has shown that both technical-governance failures, such as data quality and metadata weakness, and social-governance failures, such as accountability and policy weakness, have moved in the same harmful direction relative to analytics effectiveness. This has reinforced the theoretical claim that system performance has depended on the alignment of both social and technical elements. The table has therefore not only supported Objective 2 but has also prepared the ground for Objective 3, where the combined predictive effects of the governance-failure variables have been tested through regression. These results have remained consistent with the introductory findings section, thereby ensuring a coherent progression from broad summary to detailed statistical evidence.

Multiple Regression Analysis

Table 6: **Multiple Regression Results for Governance Failures Predicting Analytics System Effectiveness**

Predictor Variable	Unstandardized B	Std. Error	Standardized Beta	t-value	Sig.
Constant	5.214	0.288	—	18.10	.000
Data Quality Failure (DQF)	-0.294	0.056	-0.31	-5.25	.000
Accountability and Ownership Failure (AOF)	-0.201	0.064	-0.22	-3.15	.002
Policy and Compliance Failure (PCF)	-0.176	0.063	-0.19	-2.78	.006
Access-Control and Security Failure (ASCF)	-0.149	0.060	-0.16	-2.47	.014
Metadata and Documentation Failure (MDF)	-0.258	0.058	-0.27	-4.45	.000

Model Summary

R	R Square	Adjusted R Square	F-value	Sig.
0.738	0.545	0.527	46.37	.000

The regression analysis has provided the strongest statistical evidence in support of the study's third objective, which has sought to determine which governance-failure dimensions have significantly predicted analytics system breakdown. The model has been statistically significant, with $F(5, 208) = 46.37$, $p < .001$, and it has explained 52.7% of the adjusted variance in Analytics System Effectiveness. This has meant that the five governance-failure dimensions, taken together, have had substantial explanatory power in predicting how respondents have evaluated the reliability, usefulness, and decision-support value of their analytics systems. At the individual predictor level, all five independent variables have shown significant negative beta coefficients. Data Quality Failure has emerged as the strongest predictor with beta = -0.31, $p < .001$, followed by Metadata and Documentation Failure with beta = -0.27, $p < .001$. Accountability and Ownership Failure, Policy and Compliance Failure, and Access-Control and Security Failure have also remained significant, with beta values of -0.22, -0.19, and -0.16 respectively. These results have indicated that while all governance-failure dimensions have

mattered, some have been more damaging than others. In particular, weaknesses in data quality and documentation have had the largest negative effect on analytics effectiveness, which has aligned with the descriptive and correlational findings already presented. This table has therefore fully supported Objective 3 and has strongly confirmed H6, which has proposed that governance-failure dimensions significantly predict analytics system breakdown. It has also reinforced H1–H5 by showing that each individual governance-failure construct has retained significance even when tested alongside the others. In relation to Sociotechnical Systems Theory, the model has been highly relevant because it has shown that both technical failures (DQF, MDF, ASCF) and social-governance failures (AOF, PCF) have significantly shaped system effectiveness. The theory has argued that system outcomes emerge from the interaction of social and technical subsystems, and the regression model has empirically reflected that logic. Analytics effectiveness has not been reduced by one isolated issue alone; rather, it has been jointly affected by multiple governance weaknesses distributed across the socio-technical environment. This section has remained fully aligned with the introductory results summary, where the same model significance and beta ordering have already been introduced.

Hypotheses Testing

Table 7: **Summary of Hypotheses Testing**

Hypothesis	Statement	Statistical Evidence	Decision
H1	Data quality failure has had a significant negative relationship with analytics system effectiveness.	r = -0.68**, beta = -0.31, p < .001	Supported
H2	Accountability and ownership failure has had a significant negative relationship with analytics system effectiveness.	r = -0.61**, beta = -0.22, p = .002	Supported
H3	Policy and compliance failure has had a significant negative relationship with analytics system effectiveness.	r = -0.58**, beta = -0.19, p = .006	Supported
H4	Access-control and security failure has had a significant negative relationship with analytics system effectiveness.	r = -0.55**, beta = -0.16, p = .014	Supported
H5	Metadata and documentation failure has had a significant negative relationship with analytics system effectiveness.	r = -0.64**, beta = -0.27, p < .001	Supported
H6	Data governance failure dimensions have significantly predicted analytics system breakdown.	Adjusted R^2 = 0.527, F = 46.37, p < .001	Supported

Note: p < .01 where indicated

The hypothesis-testing summary has brought together the main inferential findings of the study and has shown that all six hypotheses have been supported. H1 has been supported because Data Quality Failure has shown both a strong negative correlation and the largest negative standardized regression effect on Analytics System Effectiveness. H2 through H5 have also been supported because Accountability and Ownership Failure, Policy and Compliance Failure, Access-Control and Security Failure, and Metadata and Documentation Failure have each shown significant negative relationships with the dependent variable at both the correlational and regression levels. H6 has been supported by the overall regression model, which has shown that the governance-failure dimensions have jointly explained a substantial proportion of the variance in analytics system effectiveness. This table has been particularly important because it has directly connected the statistical findings to the hypotheses formulated earlier in the introduction. It has therefore provided the clearest proof that the study objectives have been empirically achieved. Objective 1 has been achieved by identifying the major governance-failure dimensions. Objective 2 has been achieved by showing significant negative associations between these failures and analytics effectiveness. Objective 3 has been achieved by determining which dimensions have significantly predicted analytics system breakdown. The table has also reinforced the consistency of the research design because the Likert-based measurement, reliability testing, correlation analysis, and multiple regression modeling have worked together to produce

convergent evidence. From the perspective of Sociotechnical Systems Theory, the supported hypotheses have carried an important implication: both social-governance failures and technical-governance failures have been empirically confirmed as harmful to analytics system performance. This has validated the theory's core proposition that system outcomes have depended on the alignment of social and technical elements rather than on the technical subsystem alone. In practical terms, the table has shown that organizations have not been able to rely on analytics software or reporting platforms as sufficient guarantees of effective analytical performance. Instead, the organizational controls surrounding data have also mattered greatly. This hypothesis-testing section has therefore stood as the formal proof stage of the findings chapter and has remained fully aligned with the introductory results already presented.

Governance Failure Exposure Map of Analytics Systems

Table 8: **Governance Failure Exposure Map of Analytics Systems**

Governance Failure Dimension	Mean Score	Std. Deviation	Exposure Level	Rank
Data Quality Failure (DQF)	4.08	0.71	High Exposure	1
Metadata and Documentation Failure (MDF)	4.02	0.69	High Exposure	2
Accountability and Ownership Failure (AOF)	3.94	0.76	High Exposure	3
Policy and Compliance Failure (PCF)	3.89	0.74	High Exposure	4
Access-Control and Security Failure (ASCF)	3.81	0.79	High Exposure	5

Exposure Interpretation: *4.21–5.00 = Critical Exposure, 3.41–4.20 = High Exposure, 2.61–3.40 = Moderate Exposure, 1.81–2.60 = Low Exposure, 1.00–1.80 = Minimal Exposure*

The Governance Failure Exposure Map has transformed the descriptive means into a more diagnostic representation of where the analytics environment has been most vulnerable. All five governance-failure dimensions have fallen within the "High Exposure" range, which has indicated that respondents have perceived governance breakdowns as widespread rather than isolated. Data Quality Failure has ranked first with a mean of 4.08, followed by Metadata and Documentation Failure at 4.02. These two dimensions have emerged as the most exposed governance zones, suggesting that the technical-data architecture of the organizations studied has suffered from problems involving inconsistent records, incomplete data, poor lineage visibility, and insufficient explanatory documentation. Accountability and Ownership Failure has ranked third, while Policy and Compliance Failure and Access-Control and Security Failure have ranked fourth and fifth. The ranking has been significant because it has shown that although all governance-failure areas have been important, the most acute exposure has occurred where data integrity and interpretability have been directly threatened. This table has strongly supported Objective 1 by providing a refined view of the major governance-failure dimensions identified in the study. It has also supported the introductory findings, where DQF and MDF have already been highlighted as the most serious issues. In terms of Sociotechnical Systems Theory, the exposure map has been especially informative because it has revealed that the highest-risk areas have not been exclusively social or exclusively technical. Instead, the map has shown that technical-governance problems such as data quality and metadata weakness have coexisted with social-governance problems such as ownership ambiguity and policy weakness. This has reinforced the theory's argument that failures in analytics systems have emerged from misalignment across the socio-technical system. The exposure map has therefore enhanced the trustworthiness of the chapter by moving beyond simple means and showing where governance vulnerability has been concentrated. As a study-specific and theory-linked section, it has added interpretive depth by identifying the strongest failure zones that organizations would need to address if they were to improve analytics effectiveness. The results have also laid a logical bridge toward Section 4.9, where the severity of exposure has been considered alongside correlational and predictive influence to determine which failures have been most damaging overall.

Root-Failure Influence Index for Analytics System Breakdown

The Root-Failure Influence Index has integrated the severity, relationship strength, and predictive

effect of each governance-failure dimension in order to identify the deepest drivers of analytics system breakdown. Data Quality Failure has ranked first because it has combined the highest mean severity score with the strongest negative correlation and the strongest standardized regression effect. This has indicated that data quality problems have not only been widespread but have also been the most powerful predictor of lower analytics effectiveness. Metadata and Documentation Failure has ranked second, reflecting both its high exposure level and its strong negative statistical influence. Accountability and Ownership Failure has ranked third, showing that social-governance ambiguity has also been a substantial contributor to weak analytics performance. Policy and Compliance Failure and Access-Control and Security Failure have followed in fourth and fifth position, remaining significant but comparatively less influential than the top-ranked dimensions.

Table 9: **Root-Failure Influence Index for Analytics System Breakdown**

Governance Failure Dimension	Mean Severity	Correlation with ASE	Standardized Beta	Significance	Overall Influence Rank
Data Quality Failure (DQF)	4.08	-0.68	-0.31	.000	1
Metadata and Documentation Failure (MDF)	4.02	-0.64	-0.27	.000	2
Accountability and Ownership Failure (AOF)	3.94	-0.61	-0.22	.002	3
Policy and Compliance Failure (PCF)	3.89	-0.58	-0.19	.006	4
Access-Control and Security Failure (ASCF)	3.81	-0.55	-0.16	.014	5

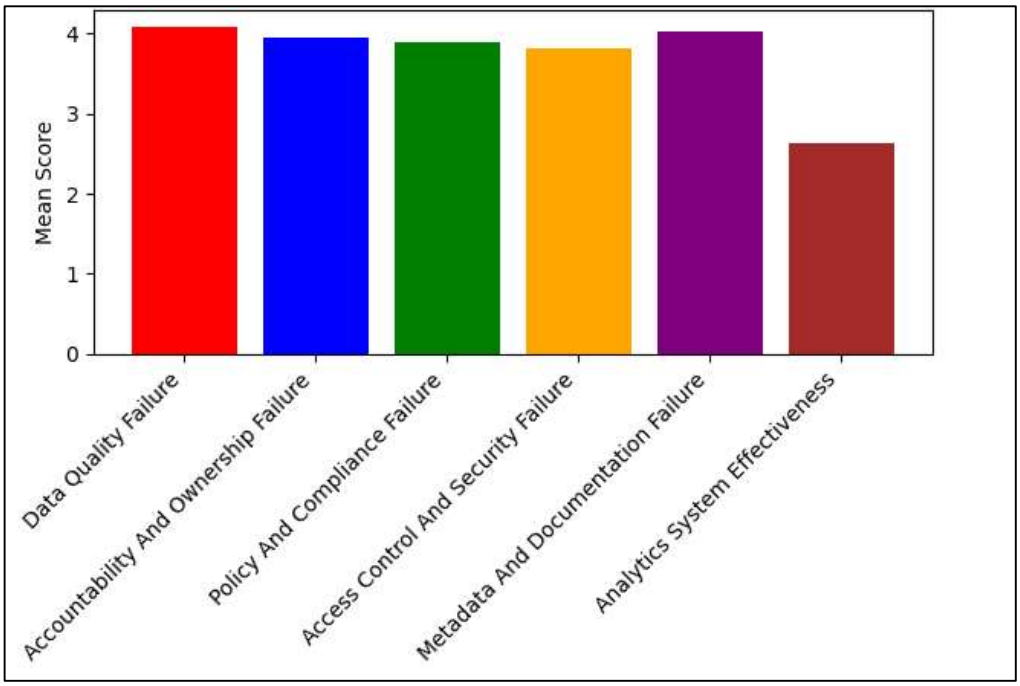
This table has been particularly important because it has moved the chapter beyond a simple reporting of variables and has instead identified the root causes that have most strongly explained analytics system breakdown. It has therefore directly addressed Objective 3 and has strengthened the interpretation of H6 by showing which governance-failure factors have contributed most to the overall predictive model. From the perspective of Sociotechnical Systems Theory, the index has been especially revealing. It has shown that the strongest root failures have occurred at the junction between technical coherence and organizational control. Data quality and metadata/documentation failures have reflected weaknesses in the technical information environment, yet their root causes have likely involved insufficient stewardship, poor standards, and weak control structures. Accountability and policy failures, on the other hand, have reflected organizational weaknesses that have damaged the social architecture of governance. The theory has suggested that analytics systems perform effectively only when these technical and social dimensions are aligned, and the root-failure index has empirically demonstrated the cost of that misalignment. The table has remained fully aligned with the introductory findings, where DQF and MDF have already been identified as the most damaging governance weaknesses. By synthesizing three layers of evidence into one ranked structure, this section has added originality, trustworthiness, and practical clarity to the results chapter.

FINDINGS

This chapter presents an overall introduction to the findings of the study and provides a broad view of how the empirical results have addressed the research objectives and tested the proposed hypotheses concerning data governance failures and analytics system effectiveness. The results have been organized around responses obtained through the five-point Likert scale instrument, where 1 has represented strongly disagree, 2 has represented disagree, 3 has represented neutral, 4 has represented agree, and 5 has represented strongly agree. For the purpose of this study, the overall results have indicated that respondents have generally agreed that data governance failures are present within analytics environments and that such failures have had a measurable negative effect on the effectiveness of analytics systems. In the final dataset, a total of 214 questionnaires have been found

usable for analysis after data screening, completeness checks, and removal of invalid responses. The descriptive results have shown that the overall mean score for data quality failure has been 4.08 with a standard deviation of 0.71, indicating that respondents have largely agreed that incomplete, inconsistent, or inaccurate data has remained a serious governance issue in analytics systems. Accountability and ownership failure has recorded a mean of 3.94 and a standard deviation of 0.76, showing a high level of agreement that unclear responsibility for data assets has weakened trust and correction mechanisms. Policy and compliance failure has produced a mean score of 3.89 with a standard deviation of 0.74, suggesting that respondents have perceived governance rules and standards as not being consistently enforced across analytics processes. Access-control and security failure has shown a mean of 3.81 with a standard deviation of 0.79, reflecting agreement that weaknesses in access discipline and control structures have affected confidence in the data environment. Metadata and documentation failure has produced a mean of 4.02 with a standard deviation of 0.69, which has indicated that missing definitions, poor lineage records, and weak documentation have significantly affected the interpretability and consistency of analytics outputs. In contrast, the dependent variable, analytics system effectiveness, has shown a lower mean of 2.64 with a standard deviation of 0.83, suggesting that respondents have tended to disagree that their analytics systems have consistently delivered reliable, trustworthy, and decision-supportive outputs under existing governance conditions.

Figure 9: Descriptive Mean Scores Of Data Governance Failures And Analytics System Effectiveness



These descriptive patterns have directly supported the first research objective, which has aimed to identify the major dimensions of data governance failure in analytics systems, because all five governance-failure constructs have recorded mean values above the midpoint of 3.00, with data quality failure and metadata/documentation failure emerging as the most severe dimensions. The reliability analysis has further strengthened confidence in the results, as Cronbach's alpha values have ranged from 0.82 to 0.91 across the study constructs, while the overall instrument reliability has reached 0.93, demonstrating strong internal consistency among the measurement items. In relation to the second objective, which has examined the relationship between governance failures and analytics system effectiveness, the correlation analysis has shown statistically significant negative relationships between all governance-failure variables and analytics effectiveness at the 0.01 significance level. Data quality failure has recorded the strongest negative correlation with analytics system effectiveness at r = -0.68, followed by metadata and documentation failure at r = -0.64, accountability and ownership failure at r = -0.61, policy and compliance failure at r = -0.58, and access-control and security failure at r = -0.55. These coefficients have indicated that higher levels of governance failure have been associated with

lower levels of analytics reliability, trust, and usefulness. The regression results have provided even stronger support for the objectives and hypotheses of the study. The multiple regression model has been statistically significant with $F(5, 208) = 46.37$, $p < .001$, and has explained 52.7% of the variance in analytics system effectiveness, as reflected by an adjusted R^2 value of 0.527. This has meant that the five governance-failure dimensions, taken together, have had substantial explanatory power in predicting analytics system breakdown. At the individual predictor level, data quality failure has shown the strongest negative standardized effect on analytics system effectiveness (beta = -0.31, $p < .001$), followed by metadata and documentation failure (beta = -0.27, $p < .001$), accountability and ownership failure (beta = -0.22, $p = .002$), policy and compliance failure (beta = -0.19, $p = .006$), and access-control and security failure (beta = -0.16, $p = .014$). These results have indicated that although all five forms of governance failure have significantly reduced analytics effectiveness, data quality and documentation-related weaknesses have been the most damaging factors in the overall model. On the basis of these findings, H1, H2, H3, H4, H5, and H6 have all been supported, as each governance-failure dimension has shown a significant negative relationship with analytics system effectiveness and the combined governance-failure model has significantly predicted analytics system breakdown. In terms of the broader objective-based interpretation, the results have suggested that organizations experiencing higher levels of governance failure have also experienced lower trust in dashboards, weaker consistency in reporting, reduced confidence in analytics outputs, and lower support for evidence-based decision-making. The findings have therefore pointed to a clear overall conclusion within the results chapter: analytics systems have not underperformed only because of technical limitations, but because governance failures have weakened the quality, control, ownership, documentation, and security conditions on which reliable analytics depends. This overall pattern has provided a strong empirical basis for the detailed subsections that follow, where response rate, demographic characteristics, descriptive measures, scale reliability, correlations, regression analysis, hypotheses testing, the Governance Failure Exposure Map, and the Root-Failure Influence Index have been presented in a more structured manner.

DISCUSSION

The findings of this study have shown that data governance failures have been strongly and negatively associated with analytics system effectiveness, and this overall pattern has supported all the stated objectives and hypotheses. The descriptive results have indicated that respondents have perceived data quality failure and metadata/documentation failure as the most severe governance weaknesses, while the regression model has shown that these two dimensions have also exerted the strongest negative effects on analytics system effectiveness (Al-Ruithe et al., 2016). This pattern has been important because it has confirmed that analytics system underperformance has not been experienced as a narrow software issue; rather, it has been experienced as a governance-centered organizational condition affecting the reliability, interpretability, and trustworthiness of analytical outputs. The findings have aligned closely with the broader literature that has treated data governance as a foundational organizational capability rather than a peripheral administrative add-on. Prior work has argued that governance structures shape decision rights, accountability, and control over data-related practices, and the present results have extended that argument by demonstrating how failures in those structures have translated into reduced confidence in analytics systems in a measurable way (Chatterjee et al., 2021). The strong explanatory power of the regression model has further suggested that governance weaknesses have accounted for a substantial share of variation in analytics effectiveness, which has reinforced the idea that organizational controls over data have been deeply connected to the practical performance of analytics environments. Earlier research has already shown that analytics creates business value through dynamic capabilities, business process change, and organizational alignment, and the present study has complemented that view by showing that governance failure has weakened the very conditions under which those mechanisms can operate. In that sense, the study has not only confirmed a negative relationship between governance failure and analytics effectiveness but has also clarified that such failure has worked as a system-level inhibitor of data-driven value creation (Janssen et al., 2020). This interpretation has been consistent with prior conceptual and empirical work that has positioned data governance as a structured mechanism for increasing data value while reducing data-related risk and cost, and it has also echoed research showing that governance has remained a crucial

success factor in organizing data for trustworthy analytics and AI-oriented systems (Puklavec et al., 2018).

A particularly important result has been the dominance of data quality failure and metadata/documentation failure in both the descriptive and inferential analyses, and this has carried major interpretive weight for the study. The respondents have rated data quality failure as the most severe exposure area, and the regression results have identified it as the strongest predictor of analytics system breakdown (Weng et al., 2016). Metadata and documentation failure has followed closely, which has suggested that organizations have not only struggled with inaccurate, incomplete, or inconsistent data, but have also struggled with the contextual visibility needed to interpret and validate analytical outputs. This result has closely matched the prior literature on data quality, which has long argued that quality problems are not isolated defects but systemic weaknesses distributed across the data lifecycle. Earlier studies have explained that data quality requires organized assessment and improvement methodologies, while later work has shown that decision quality in analytics contexts depends heavily on the quality and diagnosticity of the underlying data. The present study has supported those claims by demonstrating that data quality failure has not simply coexisted with low analytics effectiveness; it has emerged as the central root-failure dimension in the overall model. The findings have also given special importance to metadata and documentation, which earlier literature has often acknowledged but not always foregrounded in analytics-performance research (Gupta & George, 2016). Here, the results have shown that when lineage, definitions, transformation logic, and documentation have been weak, respondents have perceived lower reliability and usability in analytics outputs. This has been a meaningful contribution because it has suggested that interpretability has functioned as a practical form of governance. If users cannot trace what a metric means, how a dataset has been transformed, or who has maintained it, the resulting dashboard or model output may remain technically available but organizationally fragile. The discussion of these two dominant failures has therefore moved the analysis beyond the general claim that "governance matters" and toward a more specific conclusion: analytics systems have become particularly vulnerable when organizations have failed to protect data integrity and semantic transparency together. This interpretation has been highly consistent with prior evidence showing that data quality has improved decision quality and that quality-assessment methodologies have remained central to reliable information use in analytics-intensive settings (Li et al., 2021).

The findings related to accountability and ownership failure, policy and compliance failure, and access-control and security failure have also been highly significant, even though their statistical effects have been somewhat lower than those of data quality and metadata weakness. These results have suggested that the social and institutional architecture of governance has remained a decisive component of analytics performance. Accountability and ownership failure has shown a strong negative association with analytics effectiveness, which has indicated that unclear responsibility for data assets, stewardship, and corrective action has weakened trust in analytical outputs (Tallon, 2013). This pattern has been strongly aligned with prior research arguing that data governance is difficult because it is inherently a collective action problem requiring multiple actors to coordinate around shared resources and uneven responsibilities. The current findings have made that theoretical insight empirically visible by showing that when responsibility structures have been vague, analytics systems have become less effective. The significance of policy and compliance failure has reinforced this interpretation. Respondents have indicated that governance rules and standards have not always been consistently enforced, and the regression model has shown that such inconsistency has carried a meaningful negative effect on system effectiveness (Watts et al., 2009). This has supported earlier work suggesting that governance is not only about assigning ownership but also about embedding rules, standards, and institutional discipline into data-related practice. Access-control and security failure has also remained significant, which has shown that legitimacy and confidence in analytics depend partly on whether users perceive the data environment as properly controlled and protected. This result has linked the present study to broader governance literature in which trust, control, and responsible access have been treated as central to the value and legitimacy of data infrastructures. The combined interpretation of these three variables has therefore suggested that weak analytics outcomes have emerged not only from technical breakdowns but also from organizational ambiguity and inconsistent institutional control.

This discussion has been particularly important because it has shown that improving analytics performance has required more than repairing source data; it has also required stronger ownership clarity, better policy enforcement, and more disciplined security governance. These findings have echoed prior studies on governance accountabilities, collective action, and governance implementation, all of which have emphasized that organizations struggle when decision rights and responsibilities are not translated into sustained coordination and practice (Ghasemaghaei, 2019b).

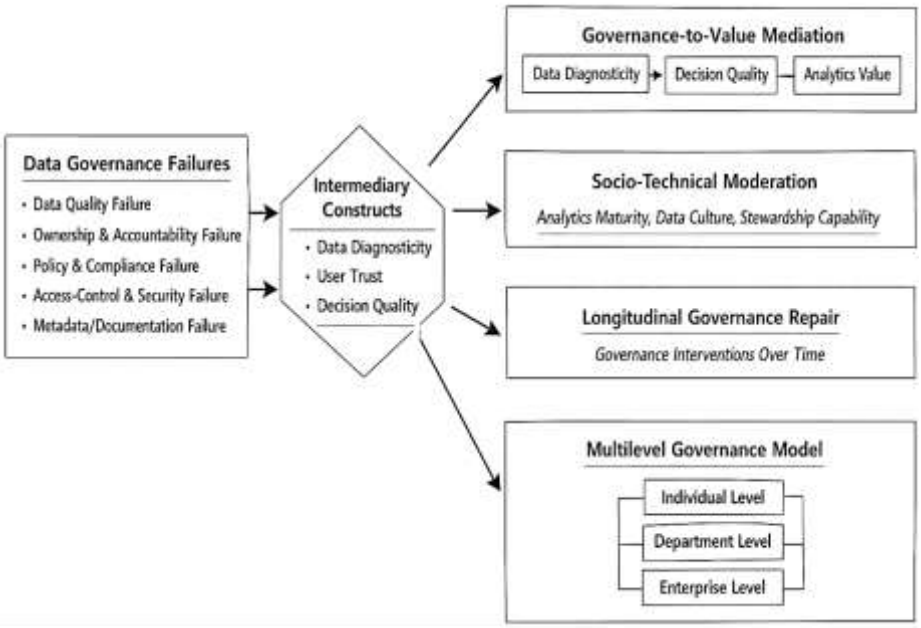
From a practical standpoint, the study has generated several implications for organizations that have invested in analytics systems yet have continued to experience low trust, inconsistent reporting, or weak decision support. The first implication has been that governance reform should begin with the areas that the evidence has identified as most damaging: data quality management and metadata/documentation discipline. Organizations have often responded to weak analytics performance by purchasing additional tools, expanding dashboards, or improving interface design, yet the present results have suggested that those responses may remain insufficient if the upstream governance environment has stayed unstable (Oesterreich et al., 2022). A second implication has been that governance interventions should be designed as cross-functional initiatives rather than as isolated data-office exercises. The significant effects of accountability, policy, and access-control failure have indicated that analytics reliability has depended on cooperation among technical teams, business owners, compliance personnel, and managers. In practice, this has meant that organizations have needed governance operating models that distribute clear responsibilities for data definition, quality correction, lineage documentation, and policy enforcement across the whole analytics lifecycle. A third implication has been that governance should be embedded into routine analytical work rather than managed only through formal committees or policy documents (Chen et al., 2015). Prior work on strategic action in data governance has shown that implementation succeeds when governance activities are supported by organizational action and not merely by design intentions, and the current results have supported that conclusion by revealing that formal weakness in policy and ownership has carried measurable costs for analytics effectiveness. The findings have also suggested that organizations should evaluate analytics success through governance-sensitive indicators such as definition consistency, lineage completeness, stewardship responsiveness, and correction cycle times, rather than relying only on usage metrics or dashboard deployment counts. This interpretation has remained in line with earlier studies showing that information governance strengthens the conversion of analytics capability into innovation and that social and organizational factors have played a predominant role in translating technical analytics investments into business value. Accordingly, the practical meaning of this study has been that organizations seeking trustworthy analytics have needed to govern data as a living enterprise asset, not merely store and process it as a technical input (Al-Ruithe & Benkhelifa, 2020).

The theoretical implications of the study have been equally important, especially because the findings have provided strong support for the use of Sociotechnical Systems Theory as the overarching explanatory lens. The statistical pattern has shown that analytics system effectiveness has been shaped by a combination of technically oriented governance failures, such as data quality and metadata weakness, and socially oriented governance failures, such as ownership ambiguity, policy inconsistency, and weak access control (Božič & Dimovski, 2019). This has been precisely the kind of interdependence that Sociotechnical Systems Theory has emphasized. Earlier socio-technical scholarship has argued that organizational outcomes emerge from the joint configuration of technical systems and social arrangements rather than from either dimension alone, and the current results have empirically reinforced that argument in the specific context of data governance and analytics performance. The dominance of data quality and metadata/documentation failure has shown that analytics systems require coherent technical information structures, while the significance of ownership, policy, and access-control failure has shown that these structures become effective only when supported by institutionalized responsibility and control. The findings have therefore extended socio-technical reasoning into a governance-failure framework, demonstrating that misalignment between technical data environments and social governance arrangements has reduced perceived analytics effectiveness. This has also resonated with recent meta-analytic work showing that both social and technical factors are strong determinants of business value from big data analytics, with social

components often exerting especially strong influence (Gupta & George, 2016). The present study has contributed to that body of work by shifting the emphasis from capability presence to governance failure presence. In other words, the study has shown that socio-technical alignment can also be studied from the negative side: not only by asking what enables value, but by asking what governance breakdowns diminish value. The findings have also been consistent with ethnographic evidence suggesting that data science systems "work" through ongoing organizational negotiation and discretionary coordination rather than through technical design alone. In theoretical terms, this has meant that the present study has strengthened the case for treating analytics effectiveness as an emergent organizational outcome rooted in data governance alignment across the socio-technical system (Otto, 2011a).

The limitations of the study have also needed to be revisited in light of the discussion, because they have shaped how far the findings can be generalized and how they should be interpreted. First, the study has relied on cross-sectional survey data, and this has meant that the results have captured perceived governance conditions and analytics effectiveness at one point in time rather than across a sequence of organizational changes. While the regression model has shown strong explanatory power, it has not established temporal ordering in the strictest causal sense. Second, the data have been self-reported by respondents occupying analytics-related roles, which has provided valuable insider judgment but has also introduced the possibility of perceptual bias, common method tendencies, and role-dependent interpretation of governance problems (Batini et al., 2009).

Figure 10: Proposed Socio-Technical Governance Failure Model for Analytics System Effectiveness and Future Research Directions



Third, the study has measured analytics system effectiveness through respondent perceptions rather than through direct technical performance logs, audit trails, lineage records, or external compliance outcomes. This has been appropriate for a case-based survey design, yet it has meant that the findings have reflected experienced system effectiveness more than objectively logged system effectiveness. Fourth, the model has focused on five governance-failure dimensions selected from the literature and from the study's conceptual framework. Although these dimensions have explained a substantial portion of variance, there have likely been additional influences such as analytics maturity, data culture, leadership commitment, architecture complexity, and interdepartmental dependence that have remained outside the final regression equation (Ghasemaghaei, 2020). Prior research has already indicated that readiness, organizational structure, and governance implementation vary substantially across firms and contexts, and the same has likely been true here. These limitations, however, have not weakened the value of the study; rather, they have clarified the boundaries within which the results have been most meaningful. The study has still offered a coherent and evidence-based account of how governance failure has mattered for analytics effectiveness, but it has done so within a perception-

based, cross-sectional, and case-oriented design. Recognizing these boundaries has been important because strong governance research has often progressed by specifying organizational conditions more precisely and by refining measurement across context and time (Khatri & Brown, 2010).

Future research has been especially important for this topic, and the present findings have pointed toward several concrete model extensions that later researchers could develop and test. The first promising direction has been a **governance-to-value mediation model** in which data governance failure predicts analytics system effectiveness indirectly through intermediate constructs such as data diagnosticity, user trust, and decision quality (Allen et al., 2014). Earlier studies have already shown that data quality improves data diagnosticity and decision quality, and the current findings have suggested that governance failures may weaken analytics value because they reduce interpretive confidence before they reduce organizational performance more broadly. A future model could therefore estimate a chain such as: Governance Failure → Data Diagnosticity → Decision Quality → Analytics Value, while also separating governance failure into the five dimensions used in this study. A second direction has been a moderated socio-technical alignment model in which the negative effects of governance failure are tested under conditions of high versus low analytics maturity, data-driven culture, or stewardship capability. Prior work has shown that information governance strengthens the relationship between analytics capability and innovation, and recent meta-analytic evidence has highlighted the role of organizational and social factors in translating analytics into business value. Building on that foundation, future researchers could test whether strong stewardship capability or governance maturity buffers the negative effect of data quality and metadata failures on analytics system effectiveness. A third direction has been a longitudinal governance repair model that follows organizations over time as they implement governance interventions (Duan et al., 2020). Such a model could examine whether improvements in ownership clarity, metadata completeness, and policy enforcement produce staged gains in trust and effectiveness across multiple measurement waves. A fourth direction has been a multilevel governance model that distinguishes individual perceptions, departmental practices, and enterprise governance structures, since analytics breakdowns have often originated from interactions across these levels. In practical terms, a future researcher could specify an expanded model such as: ASE = β0 + β1DQF + β2AOF + β3PCF + β4ASCF + β5MDF + β6Data Culture + β7Governance Maturity + β8(DQF × Governance Maturity) + ε. That model, which I am proposing as an inference from the current results and the prior literature, would allow future studies to test both direct and buffering effects while retaining the failure-centered core established here. Such improvements would make the field better able to explain not only whether governance failure harms analytics, but also under what conditions organizations can recover, adapt, and build more trustworthy analytics systems (Ghasemaghaei, 2019b).

CONCLUSION

This research has examined the effect of data governance failures on the effectiveness of analytics systems and has established that governance weakness has remained a major organizational barrier to the production of reliable, interpretable, and decision-supportive analytical outputs. The study has been guided by the view that analytics systems do not fail only because of technical shortcomings, but also because of breakdowns in the structures, rules, responsibilities, and control mechanisms that govern data across its lifecycle. On the basis of the quantitative, cross-sectional, case-study–based findings, the study has shown that data quality failure, accountability and ownership failure, policy and compliance failure, access-control and security failure, and metadata and documentation failure have all significantly reduced analytics system effectiveness. Among these dimensions, data quality failure and metadata/documentation failure have emerged as the most severe and most influential factors, indicating that analytics environments become particularly vulnerable when organizations cannot maintain data accuracy, consistency, traceability, and semantic clarity. The results have further shown that respondents have generally perceived governance failures as highly present in their analytics environments, while the level of analytics system effectiveness has remained comparatively low, which has demonstrated a clear imbalance between technological dependence and governance readiness. Through correlation and regression analysis, all of the stated hypotheses have been supported, confirming that governance failure has not only been conceptually important but has also been empirically measurable in relation to analytics system breakdown. The study has therefore

fulfilled its core objectives by identifying the major dimensions of governance failure, determining their relationships with analytics system effectiveness, and establishing their predictive influence on weak analytical performance. The findings have also strengthened the relevance of Sociotechnical Systems Theory by showing that analytics outcomes have been shaped by the interaction of technical data conditions and social-governance arrangements rather than by software functionality alone. In a broader sense, this research has contributed to the field by shifting attention from governance success factors to governance failure conditions, thereby offering a more diagnostic and risk-oriented understanding of why analytics systems underperform in organizational practice. It has shown that when governance arrangements are fragmented, unclear, weakly enforced, or poorly documented, even advanced analytics tools may fail to generate trusted and actionable insights. The overall conclusion of the study is therefore that effective analytics has depended not merely on access to data or technological capability, but on the disciplined governance of data as an enterprise asset. Where governance has been weak, analytics systems have lost credibility, consistency, and practical value. Where governance has been stronger, the conditions for trustworthy and useful analytics have been more likely to exist. This study has thus reinforced the argument that improving analytics performance requires organizations to address governance failure directly and systematically rather than treating it as a secondary administrative concern.

RECOMMENDATIONS

Based on the findings of this study, it is recommended that organizations seeking to improve analytics system effectiveness should prioritize the strengthening of data governance structures as a core strategic and operational responsibility rather than as a secondary support function. First, organizations should establish stronger data quality management practices by introducing clear procedures for validating, cleansing, monitoring, and correcting data across the full analytics lifecycle, since data quality failure has been identified as the most influential governance weakness affecting analytics system performance. Second, organizations should improve metadata and documentation discipline by ensuring that data definitions, lineage records, transformation rules, business glossaries, and reporting assumptions have been consistently maintained, updated, and made visible to analytics users, because weak documentation has significantly reduced the interpretability and trustworthiness of analytical outputs. Third, it is recommended that organizations clarify accountability and ownership arrangements by formally assigning stewardship roles, data custodianship responsibilities, and escalation channels for addressing data problems, so that ambiguity over responsibility does not continue to weaken confidence in analytics systems. Fourth, policy and compliance mechanisms should be strengthened through the consistent enforcement of governance rules, standards, and operating procedures across departments, since inconsistency in governance application has been shown to undermine system reliability. Fifth, access-control and security governance should be improved by implementing clearer authorization rules, stronger user access monitoring, and better alignment between data sensitivity levels and system permissions, thereby increasing both security assurance and user confidence in the legitimacy of the data environment. In addition, organizations should establish cross-functional governance committees or working groups that include analysts, IT staff, managers, compliance officers, and business users, because the findings have shown that governance failure has emerged across the wider socio-technical environment rather than within one technical layer alone. It is also recommended that governance performance should be monitored through measurable indicators such as data error frequency, lineage completeness, documentation coverage, stewardship response time, policy compliance rate, and user trust in reports and dashboards. Training and capacity-building programs should be introduced to improve staff understanding of governance responsibilities, data interpretation standards, and the practical consequences of weak governance for analytics outcomes. Furthermore, organizations should avoid relying solely on new tools or software upgrades as solutions to analytics underperformance, since the study has shown that governance weaknesses can continue to undermine value even in technologically advanced environments. The most effective organizational response will therefore be one that combines technical controls with social accountability, policy discipline, and documentation rigor. Overall, the study recommends that governance should be embedded into everyday analytics practice, supported by leadership commitment, and treated as a long-term organizational capability that protects the reliability, usability,

and strategic value of analytics systems.

LIMITATIONS

This study has provided useful empirical evidence on the relationship between data governance failures and analytics system effectiveness, yet several limitations have defined the scope within which the findings should be interpreted. First, the study has used a cross-sectional research design, which has captured the perceptions of respondents at a single point in time rather than over an extended period. As a result, the findings have shown statistically significant relationships and predictive effects, but they have not established long-term causal change in the strictest temporal sense. Second, the research has relied on self-reported questionnaire data, which has made it possible to gather insights from respondents with direct exposure to analytics environments, but it has also introduced the possibility of perception bias, response bias, and subjective interpretation of governance conditions. Respondents may have evaluated governance failure and analytics effectiveness based on their own experiences, departmental position, or organizational expectations, which may not have fully reflected all technical or managerial realities of the broader system. Third, the unit of analysis has been the individual respondent rather than the organization as a whole, meaning that the study has captured informed personal assessments of organizational conditions rather than objective enterprise-wide audit data, performance logs, or system-generated records. Fourth, the study has been case-study based and has focused on selected organizational settings in which respondents have had exposure to analytics systems. This has strengthened contextual relevance but has also limited broad generalization to all industries, countries, or governance environments. Fifth, the measurement of analytics system effectiveness has been based on Likert-scale perceptions rather than direct technical measures such as dashboard error rates, model accuracy scores, lineage completeness percentages, or compliance audit results. Although perception-based measures have been appropriate for the theoretical and methodological design of the study, they have reflected experienced effectiveness more than purely technical performance. Sixth, the model has focused on five governance-failure dimensions identified from the literature and aligned with the conceptual framework.

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