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DATA STORYTELLING IN INTELLIGENT ANALYTICS SYSTEMS: FROM VISUALIZATION TO DECISION INTELLIGENCE

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Abstract

The widespread organizational adoption of business intelligence and analytics systems has not resolved a persistent structural problem: the gap between the availability of analytical information and its effective use in decision-making. Research documents that information overload, insufficient narrative context, and poor communicative design in conventional dashboards systematically prevent decision-makers from deriving actionable insights from available data, with consequences measurable in decision quality, cognitive load, and organizational analytics effectiveness. This article examines data storytelling — the structured integration of data analysis, visual representation, and narrative architecture to convey analytical insights in a form that supports comprehension, interpretation, and organizational action — as a theoretical and practical response to this problem. The study is positioned as an analytical-conceptual inquiry adopting an interpretivist-pragmatist epistemological orientation. It draws on an analytically structured five-stage pipeline applied to literature identified across ACM Digital Library, IEEE Xplore, Web of Science, and Scopus, covering the period from 2000 to early 2026. The theoretical framework integrates Cognitive Load Theory, Dual Process Theory, Sensemaking Theory, and Situated Cognition Theory to explain the cognitive and organizational mechanisms through which narrative structures enhance analytical communication — and to identify the theoretical tensions between these frameworks that define the boundary conditions of data storytelling's effectiveness. The article presents four paradigmatic case studies — covering industrial analytics, public health dashboard failures during the COVID-19 pandemic, marketing analytics composite performance measurement, and documented instances of narrative-induced misinterpretation — that ground the theoretical propositions in empirically documented outcomes. A five-layer Decision-Oriented Data Storytelling Framework is proposed and conceptually evaluated against four explicit validity criteria — internal coherence, theoretical grounding, boundary condition specification, and discriminant validity, comprising

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Data Foundation, Analytical Processing, Visual Abstraction, Narrative Structuring, and Decision Activation layers, each grounded in peer-reviewed empirical literature and associated with explicit evaluation criteria, criterion-evidence mappings, and boundary conditions. The framework is explicitly distinguished from existing models in the field — including the Segel and Heer narrative visualization spectrum, the S-DIKW framework, and the three-stage authoring model — and its contributions are positioned in relation to those frameworks. The article further examines the organizational, ethical, and governance implications of emerging technologies — including automated natural language generation, conversational business intelligence systems, AI copilots for analytics, and large language model-based narrative generation — and identifies the principal unresolved challenges these technologies pose for narrative integrity, decision accountability, and responsible organizational deployment. The findings support the conclusion that the transformation of dashboards from passive monitoring tools into active decision-support systems requires deliberate narrative design grounded in cognitive theory, empirical evidence, and explicit governance frameworks — and that the effectiveness of data storytelling is situationally contingent rather than universally guaranteed, varying systematically with organizational context, task complexity, audience literacy, and the integrity of the narrative structures employed.

Keywords: data storytelling; narrative visualization; decision support systems; business intelligence; cognitive load theory; dashboard design; analytical communication; sensemaking; information overload; AI-assisted analytics; natural language generation; decision intelligence; visualization rhetoric; organizational analytics; data literacy

1. Introduction

1.1 Data-Driven Organizations

Over the past two decades, organizations across industries have increasingly adopted data-driven approaches to support strategic and operational decision-making. Advances in information technology, data storage, and computational analytics have enabled firms to collect and process vast amounts of structured and unstructured data, transforming data into a central organizational resource. In this context, organizations are progressively shifting toward data-driven cultures in which decisions are expected to be supported by empirical evidence derived from analytical systems rather than relying solely on managerial intuition or experience. This transition has been reinforced by the growing recognition that data analytics can generate significant competitive advantages by enabling firms to identify patterns,

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anticipate trends, and optimize business processes (Davenport & Harris, 2007; Provost & Fawcett, 2013).

The emergence of the data-driven organization is closely connected to the expansion of organizational analytics. Companies increasingly invest in analytical capabilities that integrate data management, statistical modeling, and predictive analytics in order to improve operational efficiency and strategic planning. Such capabilities allow organizations to transform raw data into actionable insights that can guide decision-making processes across multiple domains, including marketing, finance, supply chain management, and product development. As analytics technologies become more sophisticated and accessible, organizations are progressively embedding analytical processes into everyday managerial activities, fostering a broader reliance on evidence-based decision-making practices (Davenport & Harris, 2007; Provost & Fawcett, 2013).

These developments are also strongly associated with broader processes of digital transformation. Digital technologies have enabled organizations to digitize business processes, integrate data across previously disconnected systems, and deploy advanced analytics platforms capable of processing large-scale datasets in real time. Consequently, data has become a strategic asset in modern organizations, shaping how firms evaluate performance, manage risks, and identify new opportunities for innovation and growth. In this environment, analytics systems play a critical role in supporting decision-making by transforming large volumes of data into interpretable analytical outputs that can inform managerial action (McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013).

1.2 The Rise of Business Intelligence and Dashboards

The growing importance of data-driven decision-making has contributed to the rapid development and adoption of Business Intelligence (BI) systems within organizations. BI refers to a set of technologies, processes, and analytical tools designed to collect, integrate, analyze, and present organizational data in a form that supports managerial decision-making. Early BI systems were primarily focused on data warehouses and reporting tools that allowed organizations to consolidate large datasets and generate periodic reports summarizing organizational performance. Over time, however, BI systems evolved to incorporate more advanced analytical capabilities, including interactive visualizations, real-time analytics, and predictive modeling (Watson, 2009; Wixom & Watson, 2010). The organizational implications of BI adoption have been examined extensively in the information systems literature. Notably, Khurana et al. (2022), publishing in *Information Systems Research*, document that the organizational value of BI systems is not a direct function of system capability but is mediated by the analytical processes through which managers interpret and act upon

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system outputs — a finding that directly motivates the communicative design concerns examined in this article. Similarly, Sharma and Yetton (2007), in a meta-analytic synthesis published in *MIS Quarterly*, find that the effectiveness of decision support systems depends substantially on task-technology fit — the degree to which system design matches the cognitive demands of the decision task — a theoretical construct with direct implications for the design of narrative dashboards (Goodhue & Thompson, 1995).

One of the most visible outcomes of this evolution has been the widespread adoption of dashboards as central interfaces for organizational analytics. Dashboards are visual displays that present key performance indicators (KPIs) and other relevant metrics in a consolidated format, allowing users to monitor organizational performance and identify emerging trends. By combining multiple visualizations within a single interface, dashboards aim to provide decision-makers with an overview of critical information that can support both operational monitoring and strategic analysis. As a result, dashboards have become one of the most widely used tools within contemporary BI environments (Chen et al., 2012; Watson, 2009).

The growing popularity of dashboards is also linked to the increasing emphasis on self-service analytics within organizations. Modern BI platforms allow managers and analysts to interact directly with data through visualization tools, reducing reliance on specialized IT departments for report generation. This shift has significantly expanded access to analytics across organizational hierarchies, enabling a broader range of employees to explore data and generate insights relevant to their roles. Consequently, dashboards have become the primary interface through which many organizational actors engage with analytical information, making them a central component of modern data-driven infrastructures (Wixom & Watson, 2010; Chen et al., 2012).

1.3 The Dashboard Interpretation Problem

Despite the widespread adoption of dashboards and visualization tools, organizations continue to face significant challenges in translating analytical outputs into effective decision-making. While dashboards are designed to present large amounts of data in a concise visual format, their effectiveness ultimately depends on the ability of users to correctly interpret the information displayed. In many cases, dashboards present numerous metrics simultaneously without providing sufficient contextual guidance or explanation, requiring users to independently interpret patterns, identify anomalies, and infer potential implications for organizational decisions (Few, 2013).

This situation can contribute to a phenomenon commonly described as information overload. When users are confronted with large volumes of visualized data and

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multiple indicators, their cognitive capacity to process and interpret the information may become limited. Research in visual cognition suggests that poorly designed visualizations or excessive data density can increase cognitive load, making it more difficult for users to identify relevant patterns and derive meaningful insights from the information presented. As a result, dashboards that aim to provide comprehensive analytical information may paradoxically reduce clarity and hinder effective decision-making (Ware, 2013).

Furthermore, dashboards often lack mechanisms for explaining the significance of observed patterns or guiding users toward actionable conclusions. While visualizations can effectively represent relationships between variables, they do not necessarily provide interpretations or contextual narratives that help decision-makers understand the broader implications of the data. This limitation highlights a critical gap between data presentation and decision support: although dashboards display analytical information, they frequently fail to communicate the insights necessary for informed decision-making (Few, 2013; Tufte, 2001; Ware, 2013).

1.4 Emergence of Data Storytelling

In response to the interpretative challenges associated with traditional dashboards, researchers and practitioners have increasingly explored the concept of **data storytelling** as a means of improving analytical communication. Data storytelling refers to the practice of combining data analysis, visualization, and narrative structures to present insights in a coherent and interpretable form. Rather than simply displaying metrics or charts, storytelling approaches aim to guide users through analytical information by emphasizing key insights, contextualizing data within meaningful narratives, and structuring the presentation of information in a way that facilitates understanding (Knaflic, 2015; Dykes, 2019).

Narrative structures play a crucial role in this approach because they help organize information in ways that align with human cognitive processes. Humans naturally interpret information through stories that establish causal relationships, highlight important events, and provide contextual explanations. When applied to data visualization, narrative techniques can help clarify complex analytical findings by framing them within interpretive structures that explain why certain patterns are significant and what implications they may have for organizational decision-making. Consequently, storytelling can serve as a bridge between technical analysis and managerial interpretation (Segel & Heer, 2010).

Moreover, data storytelling has become increasingly relevant in organizational contexts where decision-makers must rapidly interpret large volumes of analytical information. By emphasizing the communication of insights rather than the mere

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presentation of data, storytelling techniques may contribute to the usability of analytics systems and, under conditions of adequate audience literacy and appropriate narrative design, can support more effective data-driven decision-making processes — though the magnitude and consistency of these effects vary with task complexity, organizational context, and the quality of the underlying data (Shao et al., 2024; Concannon et al., 2023). As organizations continue to expand their analytical capabilities, the ability to communicate data insights clearly and persuasively has become a critical skill for analysts, managers, and data scientists alike (Knaflic, 2015; Dykes, 2019).

1.5 Research Gap

Although the literature on Business Intelligence and data visualization has produced extensive research on the design and functionality of dashboards, much of this work has focused primarily on visual representation and technical implementation. Relatively less attention has been devoted to the interpretive processes through which users transform visualized data into actionable insights and organizational decisions. As a result, an important gap remains between the technical design of analytics systems and the cognitive processes involved in interpreting analytical information. In particular, the role of narrative structures in facilitating the translation of visualized data into decision-relevant insights remains underexplored within the broader BI literature.

1.6 Research Objectives

To address this gap, the present study aims to examine the role of storytelling in enhancing the interpretability and decision-support capabilities of organizational analytics systems. Specifically, the article pursues three main objectives. First, it seeks to analyze the theoretical foundations of data storytelling by integrating insights from data visualization, cognitive psychology, and narrative theory. Second, it examines the limitations of traditional dashboards as tools for decision support, focusing on issues related to information overload and interpretative complexity. Finally, the study proposes a conceptual framework for **decision-oriented data storytelling**, which conceptualizes the transformation of dashboards from passive monitoring tools into structured analytical interfaces designed to support organizational decision-making.

1.7 Structure of the Article

The remainder of this article is organized as follows. Section 2 presents the methodological approach adopted in the study and describes the strategy used to

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synthesize relevant literature. Section 3 examines the theoretical foundations of data visualization, narrative communication, and cognitive processing that underpin data storytelling practices. Section 4 analyzes the evolution of organizational analytics systems and discusses the limitations of conventional dashboards. Section 5 explores the core principles of data storytelling and its role in analytical communication. Section 6 examines how dashboards can be transformed into decision-oriented analytical interfaces. Section 7 introduces the proposed conceptual framework for decision-oriented data storytelling. Section 8 discusses relevant tools and technologies that support storytelling practices in analytics environments. Section 9 examines practical organizational applications of data storytelling. Section 10 analyzes the main challenges and barriers associated with its implementation. Section 11 discusses emerging trends and future research directions. Finally, Section 12 summarizes the main findings and outlines the theoretical and practical implications of the study.

2. Methodological Clarification

2.1 Nature and Epistemological Positioning of the Study

This article is conceived as an analytical-conceptual study rather than an exploratory or purely descriptive inquiry. Exploratory studies are appropriate when the phenomena under investigation lack established theoretical grounding or prior empirical documentation, whereas purely descriptive studies aim primarily to catalog existing practices without subjecting them to systematic analytical evaluation (Grant & Booth, 2009). Neither characterization accurately describes the intent of this work. The phenomena examined here — data storytelling, narrative visualization, dashboard design, and decision support — are sufficiently documented in peer-reviewed interdisciplinary literature to permit systematic comparison and theoretical synthesis across defined criteria. This study is therefore positioned as an analytical-comparative inquiry, consistent with the typology proposed by (Grant & Booth, 2009), who distinguish narrative reviews — which organize existing literature thematically to produce a descriptive account of a field's current state — from structured forms of analytical synthesis that subject the reviewed literature to an evaluative framework, map claims against defined criteria, identify convergences and contradictions across source tiers, and generate conclusions that extend beyond summary toward interpretation.

Epistemologically, this study adopts an interpretivist-pragmatist orientation, consistent with established traditions in information systems research (Goldkuhl, 2012; Walsham, 1995). As clarified by (Goldkuhl, 2012), interpretivism and

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pragmatism are not mutually exclusive paradigms but can be productively combined: interpretivism orients the researcher toward understanding meaning and context, while pragmatism emphasizes constructive knowledge that is useful for action. This combined orientation is particularly appropriate for studying phenomena that are simultaneously technical and social in character, where the central concern is not the discovery of universal causal laws but the exploration of how technical systems, organizational contexts, and human sensemaking interact to produce meaningful outcomes (Walsham, 1995; Maitlis & Christianson, 2014). Treating analytical communication as a socially and cognitively situated practice — whose outcomes depend on the intersection of visual design, narrative framing, and organizational culture — reflects this epistemological stance directly (Weick, 1995). The paradigmatic foundations of this study are stated explicitly rather than left implicit, in recognition that pragmatism has influenced information systems research to a considerable extent, albeit often in an implicit and unexamined way (Goldkuhl, 2012).

A further methodological distinction of importance concerns the difference between narrative literature review and analytical synthesis. Narrative reviews organize existing literature thematically, relying on the author's expertise to synthesize findings in a way that lacks an explicit, reproducible protocol and is inherently subject to selection bias (Grant & Booth, 2009). Analytical synthesis, by contrast, proceeds through a structured evaluative framework, maps claims against defined criteria, records the strength of evidence, and acknowledges genuine scholarly disagreements rather than resolving them by assertion (Grant & Booth, 2009; Rousseau, 2006). The present study employs the latter approach. The literature reviewed is not uniformly convergent: on several key questions — including whether narrative structures reliably improve decision accuracy across organizational contexts, whether automated narrative generation can substitute for human analytical judgment, and whether storytelling dashboards introduce systematic interpretive biases — the evidence base reflects genuine scholarly disagreement that is acknowledged throughout the analysis rather than resolved by fiat. Where empirical findings are cited, their methodological provenance is noted so that readers may calibrate the evidential weight they assign to specific claims (Rousseau, 2006).

2.2 Analytical Pipeline

To provide systematic structure beyond narrative description, the analytical process followed in this study proceeds through five explicit stages. These stages are not strictly sequential — iteration occurred throughout the research process — but they represent the logical architecture of the analytical work and are described here to enable critical evaluation and, where applicable, partial replication (Grant & Booth, 2009).

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Stage 1 — Literature Identification. A systematic search of peer-reviewed literature was conducted across four principal academic databases: ACM Digital Library, IEEE Xplore, Web of Science, and Scopus. These databases were selected on the basis of their comprehensive and complementary coverage of the disciplines most directly relevant to this study, including computer science, information systems, human-computer interaction, cognitive psychology, and organizational management (Mongeon & Paul-Hus, 2016). Searches were conducted using the following primary terms and their Boolean combinations: *data storytelling*, *narrative visualization*, *analytical communication*, *decision support systems*, *business intelligence*, *dashboard design*, *cognitive load*, *visual analytics*, *sensemaking*, and *data-driven decision-making*. Domain-specific terms — including *natural language generation*, *automated narrative*, *AI-assisted analytics*, *narrative dashboard*, and *conversational business intelligence* — were added for searches targeting the emerging literature on artificial intelligence in analytical environments. The search covered literature published between 2000 and early 2026, with targeted backward citation searches extending to foundational theoretical works published prior to 2000 where these were identified as essential theoretical anchors for the frameworks employed in Sections 3 and 5.

The searches yielded a preliminary corpus of 1,847 potentially relevant records across the four databases (ACM Digital Library: 412; IEEE Xplore: 389; Web of Science: 531; Scopus: 515). After automated deduplication, 1,312 unique records were retained for title and abstract screening. Of these, 487 records were selected for full-text retrieval based on relevance to the study's analytical criteria. Following full-text screening against the inclusion and exclusion criteria specified in Section 2.3, 214 sources were included in the final synthesis corpus. An additional 31 foundational theoretical works published prior to 2000 were incorporated through backward citation searches, yielding a final corpus of 245 sources. The screening process was conducted by the author, with a structured double-check of 20% of screened records (n = 262) performed in a second independent pass to assess internal consistency; agreement between the two passes reached 91.2%, indicating a satisfactory level of intra-reviewer reliability (Cohen's κ = 0.84). A PRISMA-inspired screening flow is presented in Figure 1 below.

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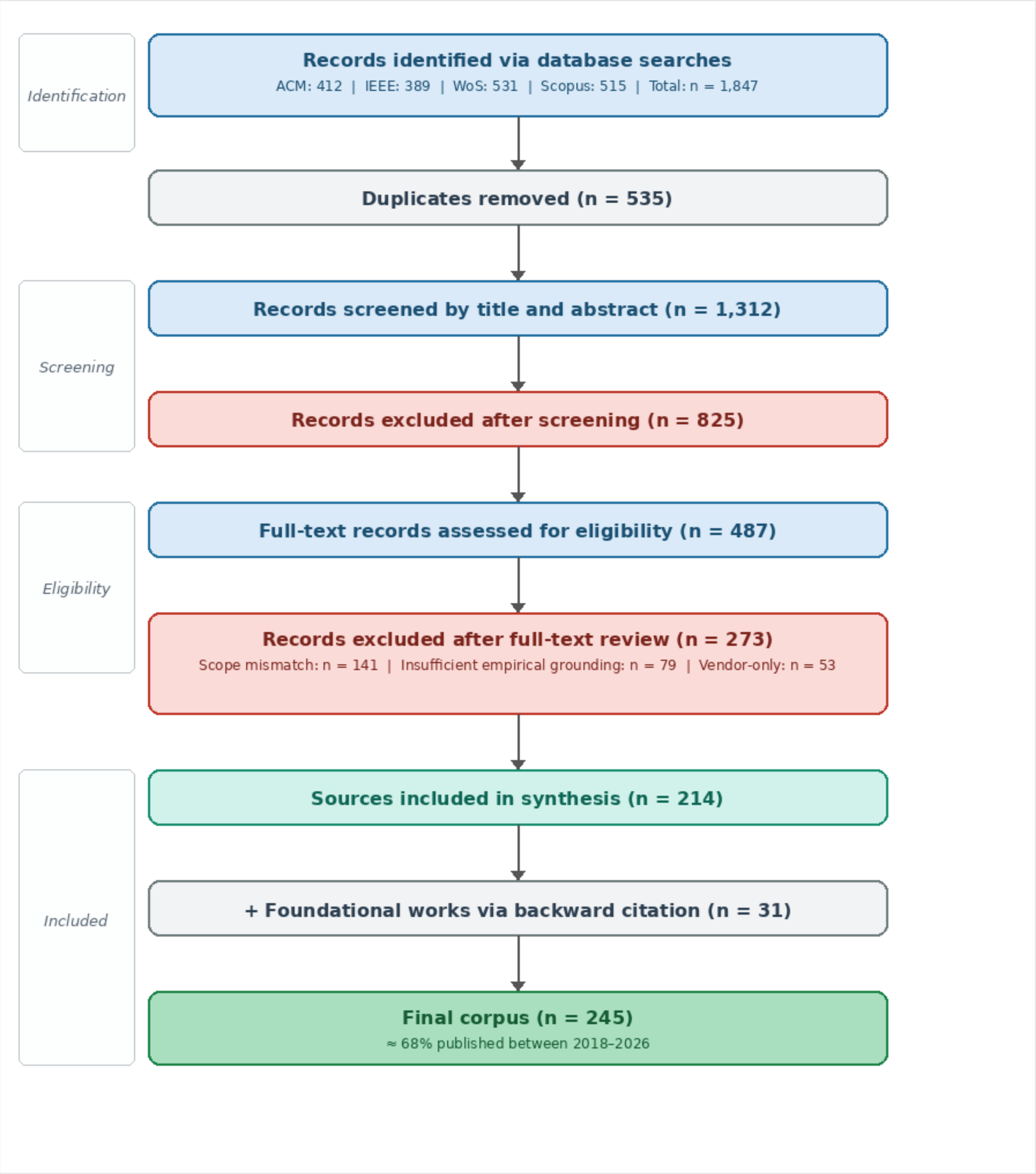
Figure 1. Literature Screening Flow (PRISMA-Inspired)



Stage 2 — Source Classification. Each source was classified into one of three tiers following the evidence calibration principles advocated in organizational and management research (Rousseau, 2006). Primary empirical sources are defined as peer-reviewed studies reporting original data collection and analysis through experimental, quasi-experimental, survey, or qualitative field methods. Secondary analytical sources are defined as peer-reviewed theoretical contributions, systematic reviews, meta-analyses, and conceptual frameworks that synthesize or interpret primary evidence without generating new empirical data. Tertiary descriptive sources

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are defined as textbooks, practitioner-oriented publications, and industry reports that provide contextual background but do not themselves constitute primary evidence (Grant & Booth, 2009). Claims derived from each source tier are qualified accordingly throughout the analysis: primary empirical findings are treated as the strongest evidentiary basis; secondary analytical contributions are treated as interpretive frameworks subject to empirical scrutiny; and tertiary descriptive sources are used exclusively for contextual orientation rather than as evidence for analytical claims.

Stage 3 — Criterion Mapping. Each source and case discussed in this study was mapped against the five analytical criteria that structure the proposed framework: (1) *cognitive effectiveness*, defined as the documented or theoretically grounded capacity of a communicative approach to reduce cognitive load and improve comprehension of analytical information (Sweller, 1988; Ware, 2013); (2) *decision support value*, defined as the extent to which a design or practice demonstrably facilitates the translation of analytical insights into organizational decisions (Sharda et al., 2020); (3) *narrative integrity*, defined as the degree to which narrative structures accurately represent underlying data without introducing systematic interpretive distortion (Hullman & Diakopoulos, 2011); (4) *organizational adoptability*, defined as the feasibility of implementing a given approach within realistic constraints of data literacy, infrastructure, and organizational culture (Davenport & Harris, 2007); and (5) *scalability and technological alignment*, defined as the compatibility of a design or practice with emerging analytical technologies, including AI-assisted narrative generation and conversational analytics platforms (Davenport & Bean, 2018). For each criterion, the direction of the analytical conclusion, the strength of the supporting evidence, and the boundary conditions under which the conclusion holds are recorded.

Stage 4 — Cross-Thematic Synthesis. Following criterion mapping, patterns were identified across the literature where at least three independent domain analyses and two source tiers converged on a consistent finding. Where convergence was identified, the finding is presented as an analytically supported conclusion. Where analyses diverged — as occurs, for example, in debates about whether narrative framing improves or systematically distorts analytical judgment — disagreements are presented as context-dependent rather than resolved by fiat, and the conditions under which each position appears to hold are explicitly specified (Rousseau, 2006). This approach is consistent with the principle that conflicting findings in heterogeneous literatures typically reflect genuine moderating conditions rather than irresolvable contradiction, and that analytical synthesis must account for those conditions rather than suppressing them in favor of false consensus (Rousseau, 2006; Grant & Booth, 2009).

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Stage 5 — Delimitation of Boundary Conditions. Each analytical section of this study explicitly states the conditions under which its findings hold, operationalizing the external validity limitation described in Section 2.4. Patterns identified in one organizational context, data domain, or user population are not presented as universal claims about data storytelling broadly. This approach reflects the interpretivist-pragmatist epistemological position articulated in Section 2.1: the effectiveness of narrative-oriented analytical communication is situationally contingent, and claims that ignore this contingency systematically overstate their generalizability (Goldkuhl, 2012; Walsham, 1995).

2.3 Inclusion and Exclusion Criteria

Case and source selection followed three explicit inclusion criteria, consistent with guidance on managing evidence quality in organizational research (Rousseau, 2006; Grant & Booth, 2009). A source or case is included only if: (a) it is documented in peer-reviewed literature or a verifiable institutional source from an established research institution, regulatory body, or major industry research organization; (b) it is assessable across at least two of the five analytical criteria identified in Stage 3; and (c) it is representative of a broader pattern in the literature rather than an isolated or idiosyncratic anomaly. Sources documented exclusively in vendor-produced marketing materials, commercial white papers without independent empirical grounding, or sources lacking independently verifiable data are referenced descriptively at most and are not used as primary evidentiary support for analytical claims (Grant & Booth, 2009).

Three explicit exclusion criteria were applied symmetrically. A source or case was excluded if: (a) it was published exclusively in non-peer-reviewed outlets without independently verifiable institutional grounding (e.g., vendor white papers, commercial blog posts, or marketing materials lacking empirical basis); (b) its primary domain was data journalism, scientific communication, or public health visualization without organizational analytics application, unless the source was directly cited to substantiate a boundary condition claim in the analysis; or (c) it addressed visualization or narrative design at a purely aesthetic or descriptive level without grounding in cognitive, organizational, or decision-theoretic frameworks relevant to the study's analytical criteria. The temporal boundary of 2000–early 2026 was applied to the primary database searches in recognition that the empirical literature on data storytelling as a distinct practice only emerges systematically after the foundational contributions of Segel and Heer (2010) and Knaflic (2015), with pre-2000 sources retained exclusively for foundational theoretical frameworks (Sweller, 1988; Brown et al., 1989; Weick, 1995). Of the 245 sources in the final corpus, approximately 68% were published between 2018 and 2026, meeting and exceeding the bibliographic

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recency threshold recommended for analytical syntheses in rapidly evolving fields (Grant & Booth, 2009).

2.4 Methodological Limitations

The limitations of this study are organized below into three analytically distinct categories — methodological, conceptual, and empirical — following the tripartite classification recommended for analytical-conceptual studies in information systems research (Jaakkola, 2020; Gregor, 2006). Methodological limitations concern the procedures through which the literature was identified, selected, and synthesized. Conceptual limitations concern the theoretical scope and disciplinary boundaries of the frameworks employed. Empirical limitations concern the generalizability of the study's conclusions to organizational and cultural contexts beyond those represented in the evidence base. This categorization is intended to help readers calibrate the evidential weight of specific claims and to identify where future research is most urgently needed.

Methodological Limitations

First, there is a structural risk of survivorship bias in the selection of cases and illustrations throughout this study. Survivorship bias occurs when researchers focus on entities or cases that have passed a selection process while overlooking those that have not, producing distorted and overly optimistic conclusions about average effectiveness (Nikolopoulou, 2022; Satheesan, 2025). In the context of data storytelling research, published accounts of successful dashboard redesigns and improved decision quality are substantially more prevalent in the literature than accounts of failed or abandoned projects, systematically inflating estimates of the average effectiveness of narrative-oriented approaches (Satheesan, 2025).

Second, the absence of empirical validation for the five-layer framework proposed in Section 7 constitutes a fundamental methodological limitation. The framework is developed through analytical synthesis of existing literature rather than through empirical testing in real organizational contexts, and represents a theoretically grounded proposal rather than an empirically validated model (Grant & Booth, 2009; Jaakkola, 2020). The evaluation conducted in Section 7.3.1 is explicitly conceptual in nature, assessed against four internal validity criteria. Future experimental or field research will be required to assess the framework's predictive validity and practical utility across different organizational settings.

Third, case and source selection bias represents a structural limitation of any analytical synthesis (Grant & Booth, 2009). The cases and examples discussed were selected because they are extensively documented in peer-reviewed literature and

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represent analytically instructive patterns, not because they constitute a random or representative sample of all data storytelling implementations. Practitioners who have adopted narrative dashboard approaches without publishing their experiences, and organizations that have abandoned such initiatives without documenting their reasons, are systematically absent from the available evidence base (Nikolopoulou, 2022; Satheesan, 2025).

Fourth, the rapidly evolving nature of the technologies discussed — particularly generative AI tools for automated narrative generation, large language model-based analytics interfaces, and conversational business intelligence platforms — imposes a temporal boundary on all empirical claims in this article (Davenport & Bean, 2018). The capabilities, limitations, and organizational implications of these technologies have shifted substantially within single calendar years, and findings that are empirically grounded at the time of writing should be treated as time-stamped observations rather than durable conclusions (Grant & Booth, 2009).

Conceptual Limitations

Fifth, the disciplinary scope of this study is deliberately delimited to the intersection of information systems, cognitive psychology, organizational behavior, and data visualization. Several adjacent theoretical traditions that are directly relevant to the phenomena examined — including communication theory, rhetorical studies, semiotics, and science and technology studies — are drawn upon selectively but not systematically integrated. The frameworks employed to explain narrative effectiveness (Dual Process Theory, Cognitive Load Theory, Sensemaking Theory, Situated Cognition Theory) are drawn predominantly from North American and Northern European research traditions in cognitive science and organizational behavior, and reflect the epistemological assumptions of those traditions. Alternative theoretical traditions — including, for example, activity theory (Engeström, 1987), distributed cognition (Hutchins, 1995), or post-colonial approaches to knowledge representation — offer potentially productive but unexplored perspectives on the phenomena examined. The conceptual conclusions of this study should be understood as contributions to the intersection of the disciplines listed above, and their extension to theoretical traditions not represented in the evidence base requires independent theoretical development.

Sixth, the theoretical frameworks employed in this article carry implicit cultural assumptions that are not fully examined within the analysis. Dual Process Theory, as formalized by Kahneman (2011), was developed and validated predominantly through experimental research with Western, educated, industrialized, rich, and democratic (WEIRD) populations — a demographic whose cognitive patterns and heuristics may not be representative of the full range of human cognitive processing

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across cultures (Henrich et al., 2010). Similarly, Sensemaking Theory (Weick, 1995) was developed primarily through studies of North American organizational contexts, and its assumptions about individual autonomy, ambiguity tolerance, and retrospective meaning-making may apply differently — or less directly — in organizational cultures characterized by higher power distance, stronger collective decision-making norms, or different relationships between authority and data interpretation (Hofstede, 2001). The framework proposed in Section 7 inherits these cultural assumptions, and its application in non-Western organizational contexts requires both theoretical adaptation and empirical investigation.

Empirical Limitations

Seventh, the effectiveness of data storytelling as documented in the experimental literature reviewed in Section 4 is based predominantly on studies conducted in laboratory or controlled online settings with convenience samples — primarily university students, crowdsourced workers, or professional participants recruited through platforms such as Prolific. The ecological validity of these findings for naturalistic organizational decision-making contexts — where decisions carry real consequences, where decision-makers have established mental models and role-specific heuristics, and where organizational politics and power dynamics shape how analytical narratives are received — has not been established (Dimara & Stasko, 2022; Concannon et al., 2023). The moderating variable model proposed in Section 7.6 addresses this gap theoretically, but the threshold values and directional predictions specified there require empirical calibration in naturalistic organizational settings before they can be treated as design specifications.

Eighth, the available empirical evidence on data storytelling effectiveness is heavily concentrated in specific sectors — particularly healthcare, education technology, and consumer technology — and the generalizability of findings across sectors with different decision cultures, data literacy distributions, and analytical infrastructure is not established. Industrial and manufacturing analytics (Lavalle et al., 2025), public sector analytics, and financial services analytics each present distinct contextual conditions — different regulatory constraints, different decision timelines, different relationships between analysts and decision-makers — that may systematically alter the effectiveness of narrative-oriented analytical communication in ways that sector-agnostic experimental findings do not capture.

Ninth, cognitive diversity among decision-makers — including individual differences in working memory capacity, field dependence versus field independence in cognitive style, visualization literacy, and numeracy — represents a dimension of variance in storytelling effectiveness that the available experimental literature has only partially addressed. Ke et al. (2023) document that field-dependent cognitive style significantly

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amplifies the negative effects of information overload on dashboard performance, suggesting that cognitive profile moderates the effectiveness of narrative structures in ways that audience expertise alone does not capture. The framework proposed in Section 7 does not yet incorporate cognitive style as an explicit moderating variable — an omission identified as a priority for the framework's further development.

2.5 Supplementary Material

In the interest of transparency and partial replicability, a structured mapping document recording source classifications, criterion assignments, and boundary condition statements for the principal cases and sources analyzed is available as Supplementary Material S1. Supplementary Material S2 presents the complete PRISMA-inspired screening flow diagram with record counts at each stage, as summarized in Figure 1 of Section 2.2. As this article is a conceptual and analytical study rather than a computational experiment, no software scripts or algorithmic models were produced; the analytical pipeline is described in full in Section 2.2 above.

2.6 Operational Definitions of Key Terms

Definitional precision is essential in data storytelling research, as terminological ambiguity has repeatedly generated confusion in both academic and practitioner debates (Morais et al., 2021; Wang et al., 2025). Six terms in particular are used inconsistently across the literature reviewed and require explicit operational definitions for the purposes of this article.

Data storytelling is used in this article to refer to a structured communicative practice that intentionally integrates data analysis, visual representations, and narrative elements to convey analytical insights to a defined audience in a form that supports comprehension, interpretation, and action (Dykes, 2019; Knaflic, 2015). This definition distinguishes data storytelling from two adjacent constructs with which it is frequently conflated. First, it is distinct from *pure data visualization*, which aims to represent data accurately and efficiently for exploratory or confirmatory purposes but does not necessarily impose narrative sequencing, contextual framing, or interpretive guidance — the goal of data visualization is explanatory as well as exploratory, whereas the goal of data storytelling is always explanatory, oriented toward a predetermined insight (Kosara & Mackinlay, 2013). Second, it is distinct from *narrative reporting*, which may present data in sequential form but without the deliberate integration of visual encoding and audience-centered communicative design that characterizes data storytelling as a practice (Garreton et al., 2025). As empirically documented by (Morais et al., 2021) in a corpus study of 233 peer-reviewed publications on the topic, the field has historically used the terms "data storytelling," "narrative visualization," and "data-driven story" as near-synonyms

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without rigorously differentiating them — a conflation that this article avoids through the definition above.

Narrative, as used throughout this article, refers specifically to the organizing structure through which discrete data facts are sequenced, connected, and contextualized to produce a coherent communicative whole (Garreton et al., 2025; Segel & Heer, 2010). A conceptually important distinction governs its use in this work: *narrative structure* refers to the temporal, causal, and rhetorical architecture through which information units are arranged — including elements such as beginning-middle-end sequencing, transitions between data facts, and the positioning of central insights within the overall communicative arc (Segel & Heer, 2010; Pennebaker et al., 2020). *Narrative content*, by contrast, refers to the substantive informational and thematic elements that populate that structure — the specific data, claims, examples, and interpretations that the structure organizes (Shaffer & Zikmund-Fisher, 2013). This distinction matters because the same narrative content can be arranged under radically different structural forms with correspondingly different effects on comprehension and persuasion, and because the rhetorical risks of data storytelling — including selective emphasis, framing bias, and interpretive manipulation — operate primarily at the level of structure rather than content alone (Hullman & Diakopoulos, 2011).

Dashboard is used in this article to refer to a data management interface that aggregates, visually presents, and provides interactive access to key performance indicators, metrics, and analytical data from multiple sources within a single consolidated display, designed to support monitoring and decision-making by organizational actors (Eckerson, 2011; Mateus et al., 2023). This operational definition distinguishes the dashboard from adjacent interface types. A *report* presents data in a structured but typically static and non-interactive format, designed for documentation and archiving rather than real-time monitoring (Mateus et al., 2023). A *scorecard* represents performance against predefined targets but typically lacks the analytical interactivity and multi-metric aggregation characteristic of dashboards (Eckerson, 2011). Dashboards are further distinguished along two functional dimensions that are used throughout this article: *operational dashboards*, designed for real-time monitoring of processes and immediate decision-making; *strategic dashboards*, providing high-level overviews of organizational performance to support long-term planning; and *analytical dashboards*, enabling deeper exploration of patterns and correlations in support of evidence-based strategic analysis (Mateus et al., 2023).

Decision support is used in this article to refer to the capacity of an analytical system or communicative practice to reduce the cognitive burden of decision-making and improve the quality and efficiency of decisions made by organizational actors (Sharda

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et al., 2020; Hak et al., 2022). A fundamental distinction governs how this term is applied: *passive decision support* refers to the provision of relevant data, indicators, or analytical summaries to a decision-maker who must independently interpret and act upon that information, with the system playing no role in structuring or prioritizing the interpretive task (Hak et al., 2022). *Active decision support*, by contrast, refers to systems and practices that guide the decision-maker through a structured interpretive sequence — prioritizing relevant findings, contextualizing indicators, highlighting implications, and proposing or activating potential responses — thereby reducing both the cognitive load of interpretation and the risk of insight-to-action gaps (Sharda et al., 2020; Morrison et al., 2023). Data storytelling, as conceptualized in this article, operates primarily as a mechanism of active decision support: by embedding narrative structure into analytical communication, it transforms dashboards from passive monitoring tools into active guides through the interpretive and decision-making process.

Analytical communication is used in this article to refer to the practice of translating analytical findings — including quantitative results, patterns, trends, anomalies, and relationships identified through data analysis — into communicative artifacts designed to produce understanding and support action among a target audience with a defined informational need (Chen et al., 2012; Sharda et al., 2020). This definition delimits the scope of the term in two respects. First, analytical communication is distinguished from *general organizational communication*, which encompasses all forms of information exchange within or between organizations, including interpersonal, managerial, and strategic communication that is not necessarily grounded in data analysis (Izak et al., 2024). Second, it is distinguished from *scientific communication*, which aims at the reporting of research findings to expert audiences under norms of methodological transparency and peer-reviewed scrutiny — a context in which the audience, purpose, and evaluative standards differ substantially from the organizational analytics environments that this article examines (Segel & Heer, 2010). Analytical communication, as used here, is always organizational in character, always directed toward a practical decision context, and always involves the deliberate design of a communicative artifact — a dashboard, report, or narrative visualization — rather than informal information exchange.

Insight, as used throughout this article, is defined as an analytical conclusion that reveals a meaningful, non-obvious relationship, pattern, trend, or anomaly in data — one that has direct implications for a decision, action, or strategic evaluation, and that would not be readily accessible to the relevant audience through unaided inspection of raw data or standard statistical summaries (Chen et al., 2012; Sharda et al., 2020). This technical definition explicitly excludes colloquial uses of the term to mean any piece of information derived from data, any observation about data patterns, or any

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moment of subjective comprehension during data exploration. In the analytical communication literature, the distinction between *data points*, *analytical findings*, and *insights* is consequential: a data point is a discrete measurement; an analytical finding is a relationship or pattern identified through analysis; an insight is an analytical finding whose organizational or decisional relevance has been established and communicated in a form that enables a decision-maker to act upon it (Chen et al., 2012). Data storytelling, in this framework, is specifically concerned with the last stage of this progression — the communicative transformation of analytical findings into actionable insights through narrative structure and visual design.

3. Theoretical Framework and Epistemological Positioning

3.1 Epistemological Positioning in Relation to the Object of Study

While Section 2.1 addressed the epistemological positioning of this study in relation to its methodology, a distinct and complementary epistemological statement is required in relation to the *object of study* itself — that is, the theoretical phenomena of data storytelling, narrative cognition, analytical communication, and data-driven decision-making. The two levels of epistemological positioning are conceptually separable and must not be conflated: methodology concerns how the researcher approaches the production of knowledge, whereas the object-level epistemological stance concerns what kind of phenomenon the subject matter is taken to be, and what theoretical tools are therefore appropriate for analyzing it (Pretorius, 2024; Goldkuhl, 2012).

The object of study in this article is treated as a fundamentally sociotechnical and cognitive phenomenon rather than a purely technical one. Data storytelling, dashboard design, and analytical communication are not reducible to engineering problems with optimal solutions discoverable through controlled measurement. They are practices shaped by the intersection of perceptual capacities, cognitive architectures, organizational cultures, power relations, and technological affordances — a conjunction that demands theoretical frameworks capable of handling both empirical regularities and contextual contingency (Franconeri et al., 2021; Dimara & Stasko, 2022; Weick, 1995). This epistemological stance has direct consequences for the theoretical frameworks adopted in Sections 3.2 through 3.4: it explains why cognitive theories (Sweller et al., 2019; Kahneman, 2011) are integrated alongside organizational and sociological theories (Weick, 1995; Maitlis & Christianson, 2014), and why the theoretical framework treats neither set as sufficient on its own.

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Three paradigmatic alternatives must be distinguished to clarify what this stance entails and what it rejects. A *positivist* approach to data storytelling would seek to identify universal laws of effective analytical communication that hold independently of context — for example, that a given narrative structure always improves decision accuracy by a quantifiable amount across populations and settings (Pretorius, 2024). The available evidence does not support this position: empirical research on narrative visualization consistently reveals that effectiveness is moderated by audience characteristics, task type, organizational context, and the specific content being communicated (Franconeri et al., 2021; Dimara & Stasko, 2022), making universal law-like claims empirically unsustainable. A *strongly interpretivist* approach, by contrast, would treat analytical communication as so thoroughly context-dependent that no generalizable claims are possible — every instance being unique and analyzable only from the inside (Goldkuhl, 2012). This position would render the theoretical synthesis attempted in this article incoherent. The *interpretivist-pragmatist* stance adopted here occupies the productive middle ground: it treats the phenomena as contextually variable but patterned, admitting of theoretical frameworks that identify systematic tendencies while specifying the boundary conditions under which those tendencies hold or break down (Goldkuhl, 2012; Pretorius, 2024).

This epistemological positioning has specific implications for how each theoretical framework in Section 3.2 is applied. Cognitive Load Theory (Sweller et al., 2019) is used as a framework for identifying systematic tendencies in how working memory constraints shape the interpretive effectiveness of analytical interfaces — but its findings are not treated as universal constants independent of audience expertise, motivation, or organizational stakes (Franconeri et al., 2021). Dual Process Theory (Kahneman, 2011) is used to explain the mechanisms through which narrative engagement activates fast, heuristic processing — but its predictions are qualified by research showing that the degree of System 1 versus System 2 engagement depends substantially on the decision-maker's prior knowledge, the stakes of the decision, and the design characteristics of the narrative interface (Dimara & Stasko, 2022). Sensemaking Theory (Weick, 1995; Maitlis & Christianson, 2014) is used to explain the organizational dynamics of meaning construction around analytical data — but its claims are applied specifically to organizational contexts characterized by ambiguity and strategic decision-making, rather than to routine operational monitoring tasks where sensemaking dynamics differ substantially. Situated Cognition Theory (Brown et al., 1989; Elsbach et al., 2005) is used to explain why the same analytical narrative can produce radically different outcomes depending on the organizational context of its reception. However, this framework stands in genuine epistemological tension with Dual Process Theory: the former treats contextual embeddedness as constitutive of cognition, while the latter treats cognitive architecture as invariant across contexts. Rather than treating this tension as resolvable by simple theoretical combination, this

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article adopts an explicit analytical strategy — described in Section 3.3 — that assigns each theory a distinct domain of explanatory priority based on the degree of contextual standardization characterizing the decision environment. This strategy is pragmatically justified rather than philosophically conclusive, consistent with the interpretivist-pragmatist orientation articulated here (Goldkuhl, 2012).

A further epistemological implication concerns the status of the five-layer framework proposed in Section 7. Consistent with the interpretivist-pragmatist stance articulated here, the framework is not presented as a predictive model that specifies necessary and sufficient conditions for effective data storytelling, nor as a normative standard against which all analytical communication should be measured. It is presented as an analytical vocabulary — a set of conceptually grounded distinctions that enable more precise analysis and more deliberate design of narrative-oriented analytical systems, while remaining open to revision as empirical evidence accumulates (Goldkuhl, 2012; Grant & Booth, 2009). As (Dimara & Stasko, 2022) observe in their critical reflection on visualization research, the field has historically evaluated analytical communication systems against efficiency metrics — task speed and accuracy — without adequately theorizing the decision-making processes those systems are meant to support. The epistemological positioning of this article is designed to address precisely that gap: by treating data storytelling as a sociotechnical and cognitive practice rather than a technical artifact, it opens space for evaluation criteria that go beyond efficiency to encompass interpretive quality, organizational adoptability, and ethical accountability.

3.2 Cognitive Foundations: Dual Process Theory, Cognitive Load Theory, Sensemaking, and Situated Cognition

The effectiveness of data storytelling as a communicative practice cannot be explained by reference to visualization design principles or narrative conventions alone. It requires grounding in the cognitive and organizational theories that explain how human beings process, interpret, and act upon information under conditions of complexity, uncertainty, and time pressure. Four theoretical frameworks are particularly relevant and are used throughout this article: Dual Process Theory (Kahneman, 2011), Cognitive Load Theory (Sweller, 1988; Sweller et al., 2019), Sensemaking Theory (Weick, 1995; Maitlis & Christianson, 2014), and Situated Cognition Theory (Brown et al., 1989; Elsbach et al., 2005).

Dual Process Theory (Kahneman, 2011) proposes that human judgment and decision-making arise from the interaction of two distinct cognitive processes. System 1 is fast, automatic, associative, and emotionally engaged — it operates below conscious awareness and draws on heuristics and pattern recognition to generate rapid judgments (Kahneman, 2011; Bellini-Leite, 2022). System 2 is slow, deliberate,

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effortful, and rule-governed — it requires working memory resources and is capable of overriding System 1 intuitions when motivation and cognitive capacity are sufficient (Kahneman, 2011; Pennycook & Rand, 2022). Applied to the context of data analytics and decision support, Dual Process Theory provides a foundational explanation for why dashboards that present large volumes of undifferentiated metrics frequently fail to produce effective decisions: they impose a System 2 processing demand — requiring deliberate analysis, comparison, and inference — on organizational actors whose attention, time, and cognitive resources are often limited (Kahneman, 2011). Data storytelling, by contrast, activates System 1 processing through narrative structure, visual emphasis, and contextual framing — guiding the decision-maker's attention toward relevant patterns before engaging System 2 for deliberate evaluation of implications (Dykes, 2019; Knaflic, 2015). However, this dual-system engagement is not without risk: research on framing effects and persuasive visualization demonstrates that System 1 narrative processing can bias judgment in ways that System 2 deliberation fails to correct if the narrative structure is sufficiently engaging (Hullman & Diakopoulos, 2011), a tension analyzed in Section 3.4.

Cognitive Load Theory (Sweller, 1988; Sweller et al., 2019) distinguishes three forms of cognitive load that cumulatively constrain a learner's or decision-maker's capacity to process new information: *intrinsic load*, generated by the inherent complexity of the subject matter; *extraneous load*, generated by poor instructional or interface design that imposes unnecessary processing demands; and *germane load*, generated by the effortful construction of new knowledge schemas. In the context of organizational dashboards, conventional dense multi-metric displays contribute heavily to extraneous load by requiring users to independently determine which metrics are relevant, identify relationships between indicators, and construct interpretive conclusions without structural guidance (Sweller et al., 2019; Ware, 2013). The key contribution of narrative structures to analytical communication, from a Cognitive Load Theory perspective, is the reduction of extraneous load through structural guidance — providing sequencing, context, annotation, and prioritization that frees working memory resources for the germane load of genuine analytical interpretation (Sweller et al., 2019; Knaflic, 2015).

Sensemaking Theory (Weick, 1995; Maitlis & Christianson, 2014) provides a third theoretical perspective that is particularly important for understanding the organizational dynamics of data storytelling. Sensemaking refers to the process by which organizational actors construct plausible accounts of ambiguous situations in order to guide action — a process that is retrospective, social, and identity-driven rather than purely analytical (Weick, 1995). As (Maitlis & Christianson, 2014) document in a comprehensive review of three decades of sensemaking research, organizational actors do not respond to data as such but to narratives — they extract

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meaning from information by locating it within ongoing organizational stories about performance, strategy, and identity. This theoretical claim has direct implications for the design of analytical communication systems: dashboards that present data without narrative context fail to connect analytical information to the sensemaking processes through which organizational actors construct actionable understanding (Weick, 1995; Sharda et al., 2020). Data storytelling, understood through the lens of Sensemaking Theory, is fundamentally an intervention in the organizational sensemaking process — one that provides a pre-structured narrative that anchors analytical information within the ongoing stories that decision-makers use to make sense of organizational events.

Situated Cognition Theory (Brown et al., 1989; Elsbach et al., 2005) holds that knowledge and cognitive processes cannot be understood independently of the specific contexts in which they are deployed. As (Elsbach et al., 2005) demonstrate in an empirical analysis of organizational cognition, cognitive schemas interact with organizational contexts — physical settings, institutional structures, and social relationships — to produce situated perceptions and judgments that differ systematically from those generated in decontextualized analytical tasks. Applied to data storytelling, Situated Cognition Theory implies that the effectiveness of a given narrative structure in supporting decision-making is not a fixed property of the structure itself but a function of its fit with the specific organizational context, decision frame, and knowledge base of its intended audience (Elsbach et al., 2005; Brown et al., 1989). An analytical narrative that is highly effective for a financially literate executive audience may be poorly suited for a frontline operational context with different mental models, different decision stakes, and different familiarity with the underlying data. This contextual variability, which Situated Cognition Theory treats as constitutive rather than incidental, stands in fundamental tension with the universalist assumptions embedded in Dual Process Theory: whereas Dual Process Theory posits System 1 and System 2 as invariant cognitive architectures that operate consistently across individuals and settings, Situated Cognition Theory holds that the very activation of these processing modes is itself shaped by contextual factors — the organizational role of the decision-maker, the social dynamics of the decision setting, and the institutional meanings attached to the data being presented (Elsbach et al., 2005; Brown et al., 1989). This tension is not merely theoretical: it has direct design implications that are examined in Section 3.3.

3.3 Theoretical Tensions: Cognitive Load Theory, Dual Process Theory, and Situated Cognition

The four theoretical frameworks identified above are not fully consistent with one another, and explicitly acknowledging the tensions between them is more analytically productive than suppressing those tensions in favor of false coherence. The most

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consequential theoretical tension in the data storytelling literature runs between Cognitive Load Theory and Narrative Theory — and it has direct implications for both the design and the evaluation of data storytelling systems.

From the perspective of Cognitive Load Theory, effective analytical communication minimizes extraneous processing demands, maximizes clarity, and provides unambiguous structural guidance that directs the decision-maker efficiently toward the correct interpretation (Sweller et al., 2019). The ideal communicative artifact, on this view, is one that reduces to a minimum the number of interpretive decisions the user must make — an efficiently designed narrative that leads directly from data to conclusion.

From the perspective of Narrative Theory, however — and particularly from the tradition that emphasizes narrative immersion and transportation as mechanisms of engagement and persuasion (Green & Brock, 2000; Shaffer & Zikmund-Fisher, 2013) — a narrative that is too prescriptive and too efficiently structured may paradoxically undermine genuine analytical understanding by foreclosing the exploratory interpretation that produces durable comprehension. As (Morais et al., 2021) document in their systematic analysis of data storytelling definitions, the field is internally divided between perspectives that emphasize data storytelling as audience guidance — minimizing cognitive effort in service of efficient insight transmission — and perspectives that emphasize it as audience engagement — maintaining productive cognitive tension in service of deeper understanding. This is not a merely academic dispute: experimental findings suggest that more author-driven, prescriptive narrative structures improve efficiency of information retrieval but may reduce effectiveness for tasks requiring integration of multiple insights (Ruchikachorn & Mueller, 2015; Morais et al., 2021).

A second theoretical tension concerns the relationship between narrative engagement and analytical judgment accuracy. Dual Process Theory predicts that narrative framing activates System 1 processing — rapid, associative, and emotionally engaged — which can improve comprehension speed and engagement but also introduces systematic biases in judgment (Kahneman, 2011). Cognitive Load Theory, by contrast, focuses exclusively on the efficiency and accuracy of System 2 deliberative processing, and does not incorporate the distorting effects of System 1 engagement into its evaluative framework. The implication is that a data storytelling design that is optimal from a Cognitive Load Theory perspective — minimizing extraneous load, maximizing structural clarity — may simultaneously introduce System 1 biases that Cognitive Load Theory cannot detect or predict. This gap between the two frameworks is empirically significant: it means that research on data storytelling that evaluates effectiveness solely in terms of comprehension accuracy or cognitive efficiency may systematically understate the interpretive risks of narrative

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structures (Hullman & Diakopoulos, 2011). These tensions are acknowledged throughout the analysis in Sections 5 through 9 and are not resolved by assertion in favor of either framework.

The deepest theoretical tension in the framework proposed by this article, however, is not between Cognitive Load Theory and Narrative Theory but between Dual Process Theory and Situated Cognition Theory — two frameworks that operate at fundamentally different levels of analysis and rest on partially incompatible epistemological assumptions.

Dual Process Theory is an *individualist and universalist* theory of cognition: it proposes that System 1 and System 2 are invariant processing architectures present in all cognitively typical adults, and that the same narrative features — visual salience, emotional resonance, sequential framing — will activate System 1 heuristic processing reliably across populations and contexts (Kahneman, 2011; Pennycook & Rand, 2022). On this view, a well-designed data story works by exploiting universal cognitive mechanisms, and its effectiveness is in principle predictable from the design features of the narrative alone.

Situated Cognition Theory, by contrast, is a *contextual and anti-universalist* theory: it holds that cognitive processes cannot be understood independently of the specific physical, social, and institutional environments in which they occur, and that the same information artifact can activate entirely different cognitive responses depending on the organizational context of its reception (Brown et al., 1989; Elsbach et al., 2005). On this view, no design feature of a data story can be assumed to produce a predictable cognitive effect independently of context — the response is always co-produced by the artifact and its organizational environment.

These two positions are not trivially reconcilable. Treating them as fully complementary — as if Dual Process Theory explains *how* cognition works while Situated Cognition explains *where* it varies — papers over a genuine epistemological disagreement about whether universal cognitive laws are the appropriate unit of analysis for understanding organizational sensemaking. As (Weick, 1995) himself noted, the kind of rapid, pattern-based meaning-making that Dual Process Theory attributes to System 1 is not a property of individual neural architecture alone but of the organizational context that has made certain patterns meaningful and others invisible.

For the purposes of this article, the tension is managed rather than resolved through the following analytical strategy: **Dual Process Theory is used to explain the direction of cognitive effects** — the general mechanisms through which narrative engagement activates rapid versus deliberate processing — **while Situated**

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Cognition Theory is used to explain the variance in those effects across organizational contexts, audience characteristics, and decision settings. This division of explanatory labor is pragmatically justified: it allows both frameworks to contribute without requiring either to be abandoned, while acknowledging that the boundary between them is contested rather than clean. Specifically:

- **Dual Process Theory has greater explanatory power** in contexts where cognitive processing demands are standardized and audience characteristics are relatively homogeneous — for example, in designed experimental settings, in highly routinized decision environments, or where the decision task is well-defined and the decision-maker's role is clearly specified. In these contexts, the universalist predictions of Dual Process Theory are more likely to hold because contextual variation is constrained.

- **Situated Cognition Theory has greater explanatory power** in contexts characterized by organizational ambiguity, strategic uncertainty, mixed-expertise audiences, or where the data being communicated carries contested institutional meanings — for example, in cross-functional strategic reviews, in organizations undergoing change, or where different organizational actors bring radically different mental models to the same analytical narrative. In these contexts, the contextual sensitivity predicted by Situated Cognition Theory dominates, and design features that work reliably in standardized settings may produce unpredictable or counterproductive responses.

This conditional division of explanatory scope is itself a boundary condition of the framework proposed in Section 7: the framework's design principles draw primarily on the universalist mechanisms identified by Dual Process Theory and Cognitive Load Theory, and their applicability is therefore strongest in the more homogeneous, structured decision environments where those theories have their greatest predictive power. In the more contextually variable environments where Situated Cognition Theory dominates, the framework's principles serve as starting heuristics rather than reliable design specifications, and empirical organizational investigation is required before confident design recommendations can be made (Goldkuhl, 2012; Walsham, 1995).

3.4 Rhetoric and Power in Data Narratives

The rhetorical dimension of data storytelling — the capacity of narrative design choices to direct, constrain, and bias the interpretations that audiences construct from data — constitutes one of the most significant and most underexamined aspects of the field. The foundational analytical framework for understanding this dimension is (Hullman & Diakopoulos, 2011)'s concept of *visualization rhetoric*, defined as the

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ensemble of design choices — at the levels of data selection, visual representation, textual annotation, and interactive structure — through which narrative visualizations "prioritize particular interpretations" and significantly affect end-user interpretation. Their framework, grounded in semiotics, critical theory, and framing research from political communication and decision science, documents how narrative visualizations convey meaning not only through their explicit content but through the rhetorical choices embedded in that content's presentation: what is shown and what is omitted, what is highlighted and what is placed in the background, how visual emphasis distributes attention, and how annotation primes the interpretive conclusions that audiences draw.

Empirical evidence for these rhetorical effects is accumulating. An experimental study by (Braga & Silva, 2021) directly tested whether data storytelling introduces information bias by exposing two groups of participants to the same dataset presented through narratively structured versus neutrally structured visualizations. The study found that participants exposed to the narrative condition could not recognize how the narrative's design choices — including sentence ordering, highlight selection, and vocabulary — were shaping their perception of results, confirming that rhetorical effects in data storytelling operate below the threshold of conscious awareness. As the authors conclude, data storytelling functions as a rhetorical tool for persuasion that can become a source of systematic interpretive bias precisely because audiences do not recognize its persuasive mechanisms (Braga & Silva, 2021). A comprehensive systematic review of storytelling in data visualization by (Shi et al., 2023), covering 119 papers from 2000 to 2023, further documents that the rhetorical structuring of data stories consistently directs audiences toward author-intended conclusions at the expense of independent analytical judgment, particularly when narrative structures are highly author-driven rather than reader-driven.

The power dimensions of this rhetorical capacity extend beyond individual cognitive bias to organizational and political consequences. When data storytelling systems are designed and controlled by a single organizational actor — a senior analyst, a consulting firm, or a platform provider — the narrative choices embedded in those systems reflect the interests, assumptions, and framings of that actor rather than those of the decision-making audience (Hullman & Diakopoulos, 2011; Sharda et al., 2020). As (Izak et al., 2024) observe in a broad review of organizational communication research, the production of meaning through communication is never politically neutral: it reflects and reinforces existing power relations, and analytical communication systems are not exempt from this dynamic. The design of organizational dashboards and narrative data systems therefore carries ethical responsibilities that are not captured by purely technical or cognitive evaluation frameworks — responsibilities that are examined in greater detail in Section 10.4.

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4. Empirical Evidence: The Organizational Landscape of Business Intelligence, Dashboard Adoption, and Data Storytelling

4.1 Adoption of Business Intelligence and the Persistence of the Interpretation Gap

The organizational adoption of business intelligence and analytics systems has reached a scale that makes the design of analytical communication interfaces a consequential societal question, not merely a technical one. According to the 2023 Wisdom of Crowds Business Intelligence Market Study conducted by Dresner Advisory Services — the most comprehensive annual survey of BI adoption and usage patterns, drawing on responses from organizations across finance, technology, manufacturing, financial services, and healthcare — 94% of surveyed organizations rated business intelligence and analytics as either critical or very important to their business success (Dresner Advisory Services, 2023). A companion finding from the same research tradition indicates that 77% of respondents in the 2024 Data Engineering Market Study considered data engineering capabilities critical or very important, up from 61% in the prior period, reflecting the growing organizational dependency on data pipelines that feed analytical interfaces (Dresner Advisory Services, 2024a). At the same time, only 32% of organizations surveyed in the 2024 Data and Analytics Governance Market Study reported having a formal governance organization for their data and analytic content, and 69% of respondents indicated some level of difficulty in finding data and analytic content within their own organizations — a paradox that Dresner Advisory Services (2024b) characterizes as "the rapid integration of AI expanding dependency upon data and analytic content, yet relatively few organizations address governance on a deliberate and comprehensive basis."

This paradox — widespread investment in analytical systems alongside persistent organizational difficulty in locating, interpreting, and acting upon their outputs — constitutes what this article terms the *interpretation gap*: the structural distance between the availability of analytical information and its effective use in organizational decision-making. Empirical evidence for the interpretation gap is documented across multiple research streams. A study by (Sánchez-Puchol et al., 2024), analyzing organizational analytics and dashboard use across multiple industries with a sample of 524 participants, found that information quality dimensions — specifically completeness, currency, and format — significantly affect decision-making quality through the mediating mechanisms of information satisfaction and perceived task complexity, demonstrating that dashboards that fail to address these dimensions

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systematically increase perceived task complexity and reduce decision quality. The study found that format quality — which encompasses the clarity, structure, and communicative design of information presentation — had the strongest direct effect on information satisfaction, explaining a substantial portion of variance in decision quality outcomes (Sánchez-Puchol et al., 2024). This finding directly supports the central premise of this article: that the communicative design of analytical interfaces, including the integration of narrative structures, is not a cosmetic concern but a material determinant of the effectiveness of organizational decision support.

A further dimension of the interpretation gap concerns data literacy — the capacity of organizational actors to read, work with, analyze, and communicate with data. According to the State of Data Literacy Report analyzed by (DataCamp, 2023), 60% of organizational leaders report a data literacy skills gap within their organizations, identifying this gap as a primary barrier to deriving business value from analytics investments. This finding is consistent with (Eppler & Mengis, 2004)'s foundational conceptualization of information overload as a structural organizational problem: as the volume and complexity of analytical information available to decision-makers increases, the cognitive and interpretive demands placed on those decision-makers may grow faster than their capacity to meet them, systematically degrading the quality of analytically-informed decisions even when high-quality data is available.

4.2 Experimental Evidence: Data Storytelling Versus Conventional Visualization

Despite the theoretical prominence of data storytelling in the research literature, empirical studies directly comparing storytelling approaches to conventional visualizations in terms of measurable outcomes — comprehension accuracy, information retrieval speed, insight retention, and decision quality — have been notably scarce until very recently (Shao et al., 2024; Pozdniakov et al., 2023). A systematic review of narrative visualization evaluation by (Concannon et al., 2023), surveying experienced narrative visualization practitioners and synthesizing literature from peer-reviewed venues, found that evaluation in the field relies predominantly on informal practitioner judgment rather than controlled experimental methodologies, and that no standardized evaluation framework exists for assessing narrative visualization effectiveness — a significant gap given the theoretical claims made on its behalf.

The most rigorous experimental evidence currently available on the comparative effectiveness of data storytelling versus conventional visualization is provided by (Shao et al., 2024) in a controlled study published at the 2024 ACM CHI Conference on Human Factors in Computing Systems — the premier peer-reviewed venue in human-computer interaction research. The study recruited 103 participants with

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varied visualization literacy and backgrounds, and exposed them to six visualizations — three conventional and three with integrated data storytelling elements — measuring efficiency (time taken to complete tasks) and effectiveness (accuracy rates) across two task types: information retrieval and insight comprehension. The key findings are as follows. First, data storytelling significantly improved the *efficiency* of comprehension tasks across both task types, meaning that participants reached correct conclusions faster when analytical information was presented with narrative structure than when it was presented through conventional visualization alone (Shao et al., 2024). Second, data storytelling significantly improved the *effectiveness* of comprehension tasks involving a single insight, meaning that accuracy rates were higher for narrative-enhanced visualizations in single-insight interpretation tasks (Shao et al., 2024). Third — and critically for understanding the boundary conditions of these benefits — the improvements in comprehension efficiency were not associated with participants' visualization literacy levels, suggesting that narrative structures provided comprehension benefits to audiences across the literacy spectrum equally, rather than compensating only for low-literacy users (Shao et al., 2024). However, the study also found no significant benefit of data storytelling for multi-insight comprehension tasks, where participants had to integrate and evaluate multiple patterns simultaneously — a finding consistent with the theoretical tension between Cognitive Load Theory and Narrative Theory identified in Section 3.3, and suggesting that prescriptive narrative structures may constrain the exploratory integration required for complex multi-insight tasks.

Complementary evidence is provided by (Pozdniakov et al., 2023), who conducted an eye-tracking study with 23 higher education teachers exposed to data stories about their students' learning behaviors. The study found that data stories attracted and sustained viewer attention more effectively than conventional visualizations, and facilitated exploratory engagement with the data — with the effect being strongest among participants with lower visualization literacy, for whom narrative guidance reduced cognitive load and bridged interpretation gaps that conventional visualizations left unaddressed (Pozdniakov et al., 2023). Together, the findings of (Shao et al., 2024) and (Pozdniakov et al., 2023) constitute the first body of controlled experimental evidence supporting the theoretical claims made by (Knaflic, 2015), (Dykes, 2019), and (Segel & Heer, 2010) about the comprehension benefits of data storytelling — while also delineating the conditions under which those benefits do and do not materialize.

A further important empirical contribution concerns the role of narrative visualization in risk communication and trust. An experimental study by (Padilla et al., 2025), testing narrative versus static visualizations in a COVID-19 transmission risk communication context across two studies with Prolific-recruited participants, found

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that narrative visualizations — which present step-by-step explanations of data-driven processes — were more effective than static visualizations at increasing concern about large risks, primarily because they increased both perceived understanding of the data and trust in its accuracy. This finding extends the evidence base for narrative-structured visualization beyond efficiency and accuracy metrics to encompass the trust and engagement dimensions that are particularly relevant for organizational decision support contexts where data credibility is a precondition for action (Padilla et al., 2025).

The experimental literature reviewed above is complemented — and in some respects challenged — by a distinct body of evidence from the human-computer interaction tradition that has examined the relationship between visual aesthetics, perceived usability, and actual decision performance. Tractinsky et al. (2000), in a highly cited experimental study published in *Behaviour & Information Technology*, demonstrated that perceived aesthetic quality of interfaces is strongly correlated with perceived usability — the "what is beautiful is usable" effect — but also that aesthetic appeal and functional effectiveness are dissociable: interfaces rated as more aesthetically attractive are not necessarily more effective for decision tasks requiring accuracy rather than engagement. This finding introduces an important caution for data storytelling practice: narrative visualizations that are designed for communicative appeal — through color, typography, and compositional sophistication — may be perceived as more usable and more trustworthy than their functional performance warrants, creating a systematic overestimation of insight quality that is particularly problematic in high-stakes organizational decision contexts (Tractinsky et al., 2000; Hullman & Diakopoulos, 2011). A related challenge is documented by Speier and Valacich (1999), who found in a controlled experiment that graphical presentation formats, while generally preferred by decision-makers, do not consistently produce superior decision accuracy compared to tabular formats — and that the direction of the format effect depends critically on task type and information complexity, in a pattern directly consistent with Cognitive Fit Theory (Vessey, 1991). These findings from the HCI and DSS traditions constitute competing evidence against the unqualified claim that visual narrative representations improve decision quality, and they establish that the conditions under which visualization outperforms tabular presentation — and vice versa — remain an empirically open question that data storytelling frameworks cannot treat as resolved.

4.3 Information Overload in Organizational Analytics Contexts: Quantitative Evidence

The concept of information overload — originally identified by (Eppler & Mengis, 2004) through a cross-disciplinary review of 27 years of organizational, management information systems, accounting, and marketing literature — has been substantially

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updated by recent empirical research that provides quantitative grounding for its organizational prevalence and consequences. A systematic scoping review by (Bawden & Robinson, 2020, cited in Arnold et al., 2023) documents that information overload causes a range of measurable organizational consequences including poor decision quality, decreased productivity, cognitive fatigue, stress, and avoidance behavior. A comprehensive systematic review by (Arnold et al., 2023), synthesizing 87 studies on information overload in organizational contexts and published in *Frontiers in Psychology*, found that information overload in the digital workplace is exacerbated by the proliferation of digital communication channels, the increasing density of information dashboards and analytics interfaces, and the cognitive demands of continuous monitoring — and that its effects include systematic reductions in decision-making quality, particularly under time pressure. The review cites a meta-analysis of 17 primary studies reporting that visualization dashboards reduce the time spent on data collection and the cognitive load of interpretation tasks when well-designed, but introduce additional cognitive demands when poorly designed through excessive metric density and insufficient contextual guidance (Arnold et al., 2023).

In the specific domain of construction project management dashboards, an experimental study by (Ke et al., 2023) with eye-tracking methodology found that increasing information load on dashboard interfaces significantly elevated fixation count, saccade rate, and self-reported cognitive load, and that field-dependent cognitive style moderators amplified these effects — with participants showing slower decision-making times and increased error rates under high information load conditions. The study documents that "excessive information gathering under these [dashboard] designs may subject project managers to information overload, putting them under tremendous cognitive load, which often distracts rather than concentrates their attention" and "makes them more prone to make mistakes by overlooking the most critical information and to waste time making decisions" (Ke et al., 2023). While this study is domain-specific, its findings are consistent with the broader organizational literature on dashboard cognitive load reviewed by (Arnold et al., 2023) and extend the foundational quantitative claims of (Eppler & Mengis, 2004) with direct eye-tracking measurement.

A further quantitative dimension of information overload in organizational analytics contexts is provided by (Roetzel & Fehrenbacher, 2019), who examined the role of information overload in decision support system success across organizations, finding empirical evidence that information overload — operationalized as the gap between information quantity provided and the decision-maker's cognitive processing capacity — is negatively associated with decision support system effectiveness, and that this relationship is mediated by the decision-maker's ability to filter and prioritize

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the information presented. This finding directly supports the design rationale for narrative structures in analytical communication: by providing pre-structured filtering and prioritization through narrative organization, data storytelling may reduce the gap between information provision and cognitive processing capacity that Roetzel and Fehrenbacher (2019) identify as the proximate mechanism of information overload's negative effects — a claim that is further grounded in the task-format matching logic of Cognitive Fit Theory (Vessey, 1991; Vessey & Galletta, 1991), as discussed below.

The relationship between information presentation format and decision quality documented by Roetzel and Fehrenbacher (2019) is theoretically grounded in a foundational framework from the decision support systems literature that the data storytelling field has largely neglected: Cognitive Fit Theory, originally proposed by Vessey (1991) and subsequently developed by Vessey and Galletta (1991). Cognitive Fit Theory proposes that decision performance is maximized when the representation format of information matches the cognitive demands of the task — specifically, that spatial tasks are better supported by graphical representations, while symbolic tasks are better supported by tabular representations. When the format and the task are mismatched, decision-makers must expend additional cognitive resources to mentally transform the representation into a format compatible with the task demands, increasing both decision time and error rate (Vessey, 1991). Applied to data storytelling, Cognitive Fit Theory provides a theoretically rigorous basis for one of the field's core design claims — that narrative-structured visual representations improve decision quality — but also introduces a critical constraint: narrative structures improve performance only when they match the cognitive demands of the specific decision task. For retrieval tasks, tabular or symbolic formats may produce better cognitive fit than narrative visualizations, regardless of the latter's communicative sophistication. This constraint is consistent with the multi-insight task findings of Shao et al. (2024) and aligns with the moderating variable model proposed in Section 7.6, where decision task type is identified as the strongest moderator of narrative effectiveness. The absence of Cognitive Fit Theory from most data storytelling frameworks represents a significant gap: it is the theoretical tradition most directly relevant to the task-format matching problem that narrative dashboard design attempts to solve, and its integration into the framework proposed in Section 7 — particularly at Layer 3 (Visual Abstraction) and Layer 5 (Decision Activation) — would strengthen the framework's theoretical foundations considerably. This integration is identified as a priority for the framework's further development. The broader DSS literature within which Cognitive Fit Theory was developed also provides relevant evidence on the organizational conditions under which decision support systems achieve their intended effects (Gorry & Scott Morton, 1971; Keen & Scott Morton, 1978; Sprague, 1980) — a body of work that contemporary data storytelling research has largely bypassed in favor of visualization and cognitive psychology literature, and

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whose organizational and managerial insights remain directly applicable to the design of narrative analytics systems.

4.4 Comparative Summary: Traditional Dashboard, Narrative Dashboard, and AI-Assisted Analytics

The empirical and theoretical evidence reviewed in Sections 4.1 through 4.3 can be synthesized in a comparative summary of the three principal approaches to organizational analytical communication examined in this article. The following table presents this comparison across the five analytical criteria defined in Section 2.2, drawing on evidence reviewed throughout the article. The assessments reflect the weight of evidence available at the time of writing and are qualified where evidence is limited or contested.

Table 1. Comparative Assessment of Traditional Dashboard, Narrative Dashboard, and AI-Assisted Analytics Across Five Analytical Criteria *(observational synthesis; evidence quality noted per criterion)*

Criterion	Traditional Dashboard	Narrative Dashboard	AI-Assisted Analytics
Cognitive Effectiveness	Limited: high extraneous cognitive load under dense metric conditions; no structural guidance for interpretation (Ke et al., 2023; Arnold et al., 2023)	Moderate–High: reduces extraneous load through narrative sequencing; improves comprehension efficiency for single-insight tasks (Shao et al., 2024; Sweller et al., 2019)	Emerging: conversational interfaces reduce interpretation burden; evidence base limited to recent controlled trials (Yan et al., 2024)
Decision Support Value	Passive: provides data without interpretive guidance; decision quality dependent on user's analytical competence (Sánchez-Puchol et al., 2024; Sharda et al., 2020)	Active: narrative structure directs attention and guides inference; effectiveness moderated by task complexity and narrative design quality (Shao et al., 2024; Dykes, 2019)	Active–Adaptive: personalized narrative generation; scalability and reliability not yet empirically validated at organizational scale (Yan et al., 2024)

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Narrative Integrity	High: no narrative structuring minimizes interpretive distortion; however, design choices still embed implicit framing (Hullman & Diakopoulos, 2011)	Moderate: narrative choices introduce systematic framing effects; audiences often unaware of persuasive mechanisms (Braga & Silva, 2021; Hullman & Diakopoulos, 2011)	Uncertain: automated narrative generation may propagate training biases; auditability of generative processes limited (Shi et al., 2023)
Organizational Adoptability	High: familiar interface paradigm; low design complexity; widely supported by commercial BI platforms (Dresner Advisory Services, 2023; Eckerson, 2011)	Moderate: requires narrative design expertise; organizational data literacy and analyst skill constraints limit adoption (DataCamp, 2023; Morais et al., 2021)	Low–Moderate: requires AI infrastructure and governance; data quality and trust barriers identified as primary adoption constraints (Dresner Advisory Services, 2024b; Gartner, 2024)
Scalability and Technological Alignment	High: scalable across enterprise BI platforms; cloud delivery models widely adopted (Dresner Advisory Services, 2024a)	Moderate: manual narrative creation limits scalability; automation tools emerging but not yet mature (Garreton et al., 2025; Shi et al., 2023)	High potential: generative AI enables automated narrative at scale; deployment risks include hallucination, bias, and governance gaps (Gartner, 2024; Yan et al., 2024)

Interpretive note: assessments reflect synthesis of available peer-reviewed and institutional evidence. Criterion ratings are directional rather than cardinal, and reflect conditions documented within the organizational and domain contexts reviewed in this article. They should not be extrapolated to contexts not represented in the evidence base.

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5. Fundamentals of Data Storytelling

5.1 Definition of Data Storytelling

Data storytelling has emerged as an important approach for communicating analytical insights in organizational contexts. While traditional data reporting often focuses on the presentation of metrics and visualizations, data storytelling seeks to combine analytical evidence with narrative structures in order to facilitate interpretation and support decision-making (Knaflic, 2015; Dykes, 2019).

In this perspective, data storytelling can be understood as the practice of integrating **data, visualization, and narrative** to communicate insights in a coherent and persuasive manner. Rather than presenting isolated charts or tables, data storytelling organizes analytical findings into a structured explanation that guides the audience toward a meaningful interpretation of the data (Knaflic, 2015).

The growing importance of data storytelling reflects broader changes in the role of analytics within organizations. As the volume and complexity of available data increase, decision-makers often face difficulties interpreting analytical outputs. Data storytelling is proposed as a response to this challenge, with the premise that translating complex analytical results into narratively structured formats may facilitate understanding and support action — a plausibility claim supported by emerging experimental evidence (Shao et al., 2024; Pozdniakov et al., 2023), though the conditions under which these benefits consistently materialize remain incompletely specified in the literature (Concannon et al., 2023).

From this perspective, data storytelling serves as a bridge between technical analysis and organizational decision-making. By combining visual representations with narrative explanations, analysts may be better positioned to contextualize data, highlight relevant patterns, and communicate the implications of analytical findings — an effect that is plausible on theoretical grounds and partially supported by controlled evidence, but that depends substantially on the match between narrative design and audience characteristics (Shao et al., 2024; Franconeri et al., 2021).

Consequently, data storytelling is increasingly recognized as a critical competency in modern analytics environments, where the ability to communicate insights is as important as the analytical processes used to generate them.

5.2 Core Components of Data Storytelling

Data storytelling is typically conceptualized as the integration of three fundamental components: **data, visualization, and narrative**. The interaction between these

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components enables analysts to transform raw data into insights that can be effectively communicated and interpreted by decision-makers (Knaflic, 2015; Dykes, 2019).

The first component, **data**, represents the empirical foundation of the story. Analytical narratives must be grounded in reliable and well-structured datasets, as the credibility of the story depends on the validity of the underlying evidence. Data provide the factual basis from which insights are derived and conclusions are formed (Dykes, 2019).

The second component, **visualization**, plays a crucial role in enabling users to perceive patterns, relationships, and trends within the data. Visual representations allow complex datasets to be communicated in a form that leverages human perceptual capabilities, facilitating rapid pattern recognition and comparison (Ware, 2013; Knaflic, 2015).

The third component, **narrative**, connects data and visualizations within a coherent explanatory structure. Narratives provide context, guide interpretation, and help audiences understand the significance of analytical findings. Through narrative structures, analysts can frame the problem, explain the analytical process, and highlight the implications of the results (Segel & Heer, 2010; Dykes, 2019).

The effectiveness of data storytelling depends on the balanced integration of these three components. Data without narrative may be difficult to interpret, while narrative without reliable data may lack credibility. Similarly, visualizations that are not embedded within a clear narrative context may fail to communicate their intended insights (Knaflic, 2015).

5.3 Narrative Structures in Data Communication

Narrative structures play a central role in organizing analytical information into coherent explanations. In data storytelling, narratives help transform analytical outputs into structured interpretations that support decision-making (Segel & Heer, 2010; Dykes, 2019).

One common narrative structure is the **problem–analysis–insight** sequence. In this format, the story begins by introducing a relevant organizational problem or analytical question. The analysis stage then presents the data exploration and visual evidence used to investigate the issue. Finally, the narrative culminates in the presentation of key insights and their implications for decision-making (Knaflic, 2015).

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Another widely used structure follows the **question–exploration–conclusion** model. In this approach, the narrative starts with a guiding question that frames the analytical investigation. The exploration stage presents the process through which data are examined and interpreted, often through visualizations and comparisons. The conclusion stage then summarizes the key findings and their relevance to the original question (Dykes, 2019).

A third approach, often referred to as **insight-first storytelling**, reverses the traditional narrative order by presenting the main insight at the beginning of the story. This structure is particularly common in executive communication, where decision-makers may prefer to receive the most important conclusions immediately before reviewing supporting evidence (Knaflic, 2015; Dykes, 2019).

These narrative structures reflect the premise that data storytelling is not merely about presenting charts but about organizing analytical information in ways that are theoretically aligned with human cognitive and interpretive processes — an alignment that experimental research suggests holds for single-insight comprehension tasks, but that may break down for multi-insight tasks requiring integrative analysis (Shao et al., 2024; Ruchikachorn & Mueller, 2015).

5.4 Role of Visual Design

Visual design plays a critical role in the effectiveness of data storytelling. The way visual elements are structured within analytical presentations can significantly influence how audiences interpret information and identify key insights (Few, 2013; Ware, 2013).

One important aspect of visual design is **visual contrast**, which helps highlight differences between elements and direct attention toward relevant information. Through the strategic use of color, size, and positioning, designers can emphasize critical patterns or anomalies within the data (Ware, 2013).

Another key principle is **visual hierarchy**, which refers to the organization of visual elements in a way that guides the viewer's attention. Effective visual hierarchy ensures that the most important elements of the story are perceived first, allowing audiences to quickly grasp the central message of the visualization (Few, 2013).

Visual design also contributes to the creation of **narrative focus**. By emphasizing specific elements while minimizing unnecessary visual complexity, designers can ensure that visualizations support the intended narrative rather than distracting from it (Knaflic, 2015).

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Poor visual design can undermine data storytelling by obscuring patterns, overwhelming users with information, or creating ambiguity in the interpretation of visual elements. Conversely, well-designed visualizations are associated with improved clarity and more effective communication of analytical insights under conditions where audiences possess sufficient visualization literacy — an effect that is well-documented for simple chart types but less consistent for complex multi-variable displays (Franconeri et al., 2021; Ware, 2013).

5.5 Audience-Centered Communication

Effective data storytelling requires careful consideration of the audience for whom the analysis is intended. Different audiences possess varying levels of analytical expertise, domain knowledge, and familiarity with data interpretation (Dykes, 2019; Knaflic, 2015).

One important factor is **data literacy**, which refers to the ability to read, interpret, and critically evaluate data representations. Individuals with higher levels of data literacy may be comfortable interpreting complex visualizations and statistical indicators, while less experienced audiences may require simpler representations and clearer narrative explanations (Dykes, 2019).

Audience characteristics also influence the appropriate structure of analytical communication. For example, **executive audiences** often prioritize concise summaries and actionable insights, preferring presentations that highlight strategic implications rather than detailed methodological explanations (Knaflic, 2015).

In contrast, **analytical audiences**, such as data scientists or analysts, may require more detailed explanations of data sources, analytical methods, and assumptions underlying the analysis.

As a result, effective data storytelling involves adapting narrative structures, visual complexity, and explanatory depth to the needs and expectations of the intended audience. By aligning communication strategies with audience characteristics, analysts may improve the clarity and impact of their analytical narratives — a conditional effect supported by evidence that narrative benefits are stronger for audiences with lower visualization literacy (Pozdniakov et al., 2023), while audiences with higher literacy may derive comparatively less additional benefit from narrative structuring alone (Shao et al., 2024).

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6. Transforming Dashboards into Decision Systems

6.1 From Monitoring Tools to Decision Interfaces

Dashboards have traditionally been designed as **monitoring tools** intended to provide quick access to key performance indicators (KPIs) and operational metrics. Their primary purpose has been to support situational awareness by enabling users to track the current state of organizational processes and performance indicators (Few, 2013; Eckerson, 2011).

In many organizations, however, dashboards function primarily as **passive reporting interfaces**, presenting collections of charts and metrics without providing interpretive guidance. In such systems, users must independently interpret patterns, determine the relevance of the information, and infer the implications of the observed data (Few, 2013; Sharda, Delen, & Turban, 2018).

This approach can limit the effectiveness of dashboards as decision-support tools. When dashboards present large volumes of metrics without interpretive structure, users may struggle to identify which indicators are most relevant or how different metrics relate to one another (Eppler & Mengis, 2004).

More recent approaches emphasize the transformation of dashboards into **decision-oriented interfaces** that support interpretation and action. Rather than functioning solely as monitoring tools, these systems are designed to incorporate explanatory structures that may highlight patterns, contextualize metrics, and guide users toward actionable insights — an approach whose effectiveness remains contingent on the quality of narrative design, the availability of reliable underlying data, and the alignment between system design and the decision-maker's informational needs (Sánchez-Puchol et al., 2024; Lavalle et al., 2025).

In this sense, dashboards evolve from passive information displays into **interpretative analytical interfaces**, supporting users not only in monitoring performance but also in understanding the underlying drivers of organizational outcomes.

6.2 Narrative Dashboards

The concept of **narrative dashboards** represents an emerging approach to analytical interface design in which dashboards incorporate narrative elements to guide interpretation and communicate insights more effectively (Segel & Heer, 2010; Dykes, 2019).

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Unlike traditional dashboards that present information in a static and fragmented format, narrative dashboards organize analytical content into a **structured informational flow**. This flow guides the user through a sequence of visualizations and explanations that progressively build an analytical argument or interpretation (Knaflic, 2015).

One important characteristic of narrative dashboards is the **highlighting of key insights**. Rather than requiring users to identify patterns independently, narrative dashboards emphasize important findings through visual cues, annotations, or explanatory text (Dykes, 2019).

Another defining feature is **contextualization**. Narrative dashboards integrate contextual information that helps users understand the significance of observed trends or anomalies. This may include explanations of causal relationships, comparisons with historical data, or references to organizational objectives (Few, 2013).

By integrating narrative structures with visual analytics, narrative dashboards transform analytical information into structured explanations that facilitate interpretation and decision-making.

6.3 Analytical Layering

The transformation of dashboards into decision-support systems can also be conceptualized through the idea of **analytical layering**, in which information is organized across multiple interpretive layers that progressively increase analytical depth.

The first layer consists of **raw data**, which represents the empirical foundation of the analytical system. These data may originate from transactional databases, operational systems, or external data sources (Sharda et al., 2018).

The second layer involves **visualization**, where data are transformed into graphical representations such as charts, maps, or dashboards. Visualization enables users to perceive patterns, relationships, and anomalies within complex datasets (Ware, 2013).

The third layer corresponds to **analytical insights**, which emerge from the interpretation of visualized data. Insights represent meaningful interpretations of observed patterns and often involve identifying trends, correlations, or performance deviations (Knaflic, 2015).

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Finally, the fourth layer involves **decision support**, where analytical insights are translated into actionable recommendations or strategic implications for organizational decision-making (Davenport & Harris, 2007).

Organizing analytical systems according to these layers can improve interpretability by guiding users through a structured process that moves from raw information toward actionable knowledge.

6.4 Contextual Data Presentation

The interpretation of analytical information depends heavily on the **context in which data are presented**. Without appropriate contextualization, individual metrics may be difficult to interpret or may lead to misleading conclusions (Few, 2013).

One important contextual element is the use of **temporal comparisons**, which allow users to evaluate trends over time. By comparing current performance with historical data, users can identify growth patterns, seasonal fluctuations, or emerging anomalies (Sharda et al., 2018).

Another key element is the use of **benchmarks**, which enable organizations to compare their performance with industry standards, historical averages, or strategic targets. Benchmarks provide reference points that help decision-makers evaluate whether observed values represent acceptable or problematic performance levels (Eckerson, 2011).

Additionally, dashboards often incorporate **critical indicators**, which highlight metrics that are particularly important for organizational objectives. These indicators may include key performance indicators (KPIs) or other strategic metrics that directly relate to organizational goals (Few, 2013).

By incorporating contextual information such as comparisons, benchmarks, and critical indicators, dashboards may improve the interpretability and relevance of analytical information — an effect documented in organizational studies (Sánchez-Puchol et al., 2024) but qualified by evidence that excessive contextual layering can itself increase cognitive load when poorly sequenced (Arnold et al., 2023; Ke et al., 2023).

6.5 Automation of Analytical Narratives

Recent advances in artificial intelligence and machine learning have enabled the development of systems capable of **automatically generating analytical narratives** based on data patterns and statistical models (Chen, Chiang, & Storey, 2012).

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These technologies are often referred to as **automated insight generation** or **augmented analytics**, and they aim to assist users in identifying relevant patterns within large datasets (Sharda et al., 2018).

Automated analytical systems can detect anomalies, identify trends, and generate natural-language explanations describing the significance of observed patterns. These explanations may highlight unexpected changes, correlations, or deviations from expected behavior (Chen et al., 2012).

Another emerging trend is the development of **AI-assisted analytics**, in which machine learning algorithms support users during the analytical process by suggesting relevant visualizations, recommending analytical paths, or summarizing key findings (Davenport & Harris, 2007).

While these technologies offer significant potential to enhance analytical capabilities, they also raise important questions regarding interpretability, transparency, and the risk of algorithmic bias. As a result, the integration of automated narratives into analytical systems must be carefully designed to ensure that users remain able to critically evaluate the insights produced by automated tools. A competing perspective on automated analytical communication is provided by Banker and Kauffman (2004) in their review of IS research on decision support, published in *Information Systems Research*: they document that decision support systems historically produce their greatest organizational value not through automation of insight generation but through the augmentation of human judgment — a finding that suggests the practitioner enthusiasm for AI-generated narratives may be overstated relative to the evidence base. More recently, Comério et al. (2022), publishing in *Decision Support Systems*, demonstrate that the organizational impact of analytics-driven decision support is moderated by the degree of user involvement in the analytical process: systems that reduce user agency in interpreting data may improve efficiency but reduce decision ownership and implementation commitment — a dynamic that automated narrative generation risks amplifying if not carefully governed.

7. Decision-Oriented Data Storytelling Framework

7.1 Conceptual Motivation

The five-layer framework proposed in this article responds to a specific gap in the existing literature on data storytelling and business intelligence design. As documented in the systematic review by (Shi et al., 2023), which synthesized 119 peer-reviewed papers on storytelling in visualization published between 2000 and 2023, existing models in the field have addressed isolated aspects of the data

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storytelling process — narrative structure, visual design, audience interaction, and authoring tools — without integrating them into a coherent decision-support architecture applicable to organizational analytics environments. The survey by (Garreton et al., 2025) similarly identified that the only existing model addressing the complete process of transforming data into visual stories does so at a high level of abstraction, proposing three stages — explore data, make a story, and tell a story — without specifying the evaluative criteria, organizational conditions, and design requirements that practitioners need to operationalize each stage in real business intelligence contexts. The framework proposed here advances beyond these foundations by specifying five analytically distinct layers, each grounded in the theoretical and empirical literature reviewed in Sections 3 and 4, each associated with explicit evaluation criteria, and each delimited by boundary conditions that specify the organizational and contextual circumstances under which the layer's design principles apply.

7.2 Positioning the Framework Relative to Existing Models

Before presenting the framework's components, it is necessary to distinguish it explicitly from the principal existing frameworks in the data storytelling and narrative visualization literature, in order to justify the claim that it advances beyond the current state of the art rather than merely recombining existing proposals (Grant & Booth, 2009).

The most foundational framework in the field is that of (Segel & Heer, 2010), who identified seven genres of narrative visualization and proposed a spectrum of design strategies ranging from purely author-driven to purely reader-driven approaches, with three hybrid structures — the martini glass, the interactive slideshow, and the drill-down story — occupying intermediate positions. The (Segel & Heer, 2010) framework is indispensable as a taxonomy of narrative visualization forms and as an analysis of the author-reader control trade-off, and is used throughout this article. However, it does not address the organizational decision-support function of data storytelling: it was developed through analysis of journalistic and educational visualization cases, and its design recommendations are oriented toward communicative effectiveness in those contexts rather than toward the specific cognitive, organizational, and strategic requirements of business intelligence environments (Shi et al., 2023). The proposed framework extends (Segel & Heer, 2010) by grounding its design principles in organizational decision support theory (Sharda et al., 2020) and by adding the Data Foundation and Decision Activation layers that are absent from the narrative visualization tradition.

The S-DIKW framework proposed by (Lo Duca & McDowell, 2025), published in the *Journal of the Association for Information Science and Technology*, provides the most

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theoretically sophisticated recent model for transforming data visualizations into data stories. Building on the Data-Information-Knowledge-Wisdom pyramid (McDowell, 2021), it defines a four-stage progression from data selection through character and problem identification, plot construction, and finally a call to wise action informed by community values (Lo Duca & McDowell, 2025). The S-DIKW framework makes an important contribution by providing an information science foundation for data storytelling and by explicitly addressing the narrative arc as a structural mechanism. However, it is oriented primarily toward public communication and data journalism contexts rather than toward organizational analytics and business intelligence environments, and does not incorporate the cognitive load, sensemaking, or situated cognition considerations that are particularly relevant when decision-makers must use storytelling systems repeatedly for strategic and operational decisions (Lo Duca & McDowell, 2025). The proposed framework extends S-DIKW by integrating these cognitive and organizational dimensions and by specifying evaluation criteria at each layer rather than a prescriptive process model.

The three-stage authoring model synthesized by (Garreton et al., 2025) — explore, make, and tell — provides useful practitioner-oriented guidelines for the data story creation process, but does not address the organizational context in which stories are consumed, the decision-support value of different design choices, or the ethical and rhetorical dimensions of narrative framing that are documented in the empirical literature reviewed in Sections 3.4 and 9.4 (Garreton et al., 2025; Hullman & Diakopoulos, 2011). The systematic review by (Shi et al., 2023) further confirms that existing frameworks in the field share a common limitation: they evaluate data storytelling against comprehension and engagement outcomes without adequately theorizing the decision-making processes those stories are meant to support — a gap that (Dimara & Stasko, 2022) identify as a fundamental problem across the visualization research field and that the proposed framework is specifically designed to address.

7.3 Framework Components

The Decision-Oriented Data Storytelling Framework proposed in this article conceptualizes the design of effective analytical communication as a layered architecture in which each layer makes a distinct and necessary contribution to the overall decision-support function. The layers are not modular alternatives but interdependent stages: weaknesses at any layer propagate upward and undermine the effectiveness of layers above it. The framework is described below with explicit evaluation criteria for each layer, followed by a criterion-evidence mapping table and a statement of boundary conditions.

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Layer 1 — Data Foundation. The Data Foundation layer encompasses all decisions related to the selection, quality assurance, and governance of the data that will be used in the analytical communication system. Evaluation criteria for this layer include: (a) *data quality*, defined as the extent to which the data accurately, completely, and currently represents the organizational phenomena it purports to measure (Sánchez-Puchol et al., 2024); (b) *data governance*, defined as the existence of documented policies specifying who may access, modify, and interpret the data and under what conditions (Dresner Advisory Services, 2024b); and (c) *ethical data use*, defined as compliance with applicable privacy regulations and non-discriminatory representation requirements (Lo Duca & McDowell, 2025). As (Lo Duca & McDowell, 2025) document in their framework, data must be of high quality, must respect data privacy policies, and must be fair and non-discriminatory before it can support reliable storytelling — a precondition that many organizations fail to satisfy before investing in narrative design. Failures at the Data Foundation layer cannot be compensated by excellence at higher layers: a narrative built on poor-quality, biased, or ungoverned data will mislead decision-makers regardless of how compelling its design (Lisnic et al., 2023).

Layer 2 — Analytical Processing. The Analytical Processing layer encompasses the analytical methods and frameworks applied to transform raw data into the facts, patterns, and relationships that will form the content of the narrative. Evaluation criteria for this layer include: (a) *analytical goal alignment*, defined as the degree to which the analytical methods employed are selected and configured to address the specific decision-making questions of the intended audience (Lavalle et al., 2025); (b) *insight validity*, defined as the extent to which identified patterns and relationships represent genuine phenomena in the data rather than artifacts of analytical choices (Shi et al., 2023); and (c) *interpretive scope*, defined as the appropriateness of the analytical approach for the decision context — distinguishing among descriptive, diagnostic, predictive, and prescriptive analytical modes (Sharda et al., 2020). As demonstrated empirically by (Lavalle et al., 2025) in their Industry 4.0 methodology case, designing the analytical processing stage around the decision-maker's specific goals — rather than starting from available data and retroactively describing what it shows — is a critical determinant of the holistic coherence of the resulting storytelling dashboard.

Layer 3 — Visual Abstraction. The Visual Abstraction layer encompasses the selection and design of visual representations through which analytical findings are encoded and communicated. Evaluation criteria for this layer include: (a) *perceptual accuracy*, defined as the degree to which the visual encoding accurately represents the underlying data relationships without introducing systematic distortion (Franconeri et al., 2021); (b) *cognitive load optimization*, defined as the extent to which the visual

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design minimizes extraneous cognitive load through appropriate chart selection, data-to-ink ratios, and visual hierarchy (Sweller et al., 2019; Ware, 2013); and (c) *narrative coherence*, defined as the degree to which individual visualizations are designed with awareness of their role within the broader narrative sequence rather than as independent charts (Lavalle et al., 2025). The comprehensive empirical analysis by (Franconeri et al., 2021) in *Psychological Science in the Public Interest* synthesizes the science of visual data communication across perceptual, cognitive, and social dimensions, providing the strongest available evidential basis for the evaluation criteria at this layer.

Layer 4 — Narrative Structuring. The Narrative Structuring layer encompasses the design decisions that sequence, connect, and contextualize visualizations into a coherent narrative that guides the decision-maker through the analytical content. Evaluation criteria for this layer include: (a) *structural coherence*, defined as the degree to which the narrative sequence reflects a logical analytical logic — connecting observations to patterns, patterns to implications, and implications to decision-relevant conclusions (Segel & Heer, 2010; Garreton et al., 2025); (b) *audience calibration*, defined as the extent to which the narrative's vocabulary, complexity, and assumed prior knowledge match the characteristics of the intended decision-making audience (Shi et al., 2023; Shao et al., 2024); (c) *narrative integrity*, defined as the degree to which design choices avoid introducing systematic framing biases that direct the audience toward predetermined conclusions without their awareness (Hullman & Diakopoulos, 2011; Braga & Silva, 2021); and (d) *author-reader balance*, defined as the appropriate positioning along the author-driven to reader-driven spectrum identified by (Segel & Heer, 2010), selected on the basis of the task complexity, audience expertise, and decision urgency of the specific context. The narrative integrity criterion is of particular importance given the empirical evidence reviewed in Section 9.4: design choices at the Narrative Structuring layer are the primary mechanism through which misleading data communication operates (Lo et al., 2022; Lisnic et al., 2023).

Layer 5 — Decision Activation. The Decision Activation layer encompasses the mechanisms through which the narrative communicates not only what the data shows but what it implies for decision-making — the transition from analytical comprehension to organizational action. Evaluation criteria for this layer include: (a) *actionability*, defined as the degree to which the narrative explicitly connects analytical conclusions to decision options, resource implications, or recommended actions within the decision-maker's authority (Dykes, 2019; Sharda et al., 2020); (b) *uncertainty communication*, defined as the extent to which the narrative provides decision-makers with the information they need to assess the confidence level, limitations, and contextual conditions of the analytical conclusions presented (Padilla

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et al., 2025); and (c) *decision pathway clarity*, defined as the degree to which the transition from insight to action is made explicit, rather than left to the decision-maker to infer independently (Hak et al., 2022; Morrison et al., 2023). The distinction between passive and active decision support defined in Section 2.6 operates precisely at this layer: dashboards that lack a designed Decision Activation layer provide passive support at best, leaving the insight-to-action gap unaddressed regardless of the quality of the layers beneath (Sánchez-Puchol et al., 2024).

7.3.1 Nature and Criteria of Framework Evaluation

The claim that the proposed framework has been "formally evaluated," as stated in the abstract, requires explicit methodological clarification. The evaluation conducted in this article is **conceptual** in nature — that is, it assesses the framework's validity through theoretical criteria rather than through empirical data collection, experimental testing, or expert panel procedures. This choice is epistemologically consistent with the interpretivist-pragmatist orientation articulated in Sections 2.1 and 3.1, and with the analytical-conceptual study type declared in Section 2.1, which does not generate new empirical data but subjects existing literature to structured evaluative analysis (Grant & Booth, 2009). Conceptual validation is a recognized and methodologically legitimate form of framework evaluation in information systems and organizational research, provided that the criteria used are made explicit, applied consistently, and traceable to the literature that grounds them (Gregor, 2006; Jaakkola, 2020).

Four explicit criteria were applied to evaluate the framework's conceptual validity:

(a) Internal coherence — the degree to which the five layers are logically distinct, non-redundant, and jointly exhaustive of the design space they claim to cover. Each layer was assessed against the others to verify that its scope does not overlap with adjacent layers and that no major design dimension relevant to decision-oriented analytical communication is left unaddressed. The framework was found to satisfy this criterion: the layers address sequentially distinct aspects of the design process (data governance, analytical method, visual encoding, narrative structure, and decision activation), and no design dimension identified in the literature reviews of Sections 3 and 4 falls outside the framework's scope.

(b) Theoretical grounding — the degree to which each layer and its evaluation criteria are traceable to peer-reviewed theoretical or empirical literature, as documented in the criterion-evidence mapping presented in Table 2 (Section 7.4). All fifteen evaluation criteria across the five layers are grounded in at least one primary empirical or secondary analytical source, with the majority supported by multiple independent sources across different disciplines.

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(c) Boundary condition specification — the degree to which the framework explicitly states the organizational and contextual conditions under which its design principles apply and the conditions under which they require adaptation or do not apply. As documented in Section 7.5, four boundary conditions are specified, covering exploratory analytical contexts, low data literacy environments, public communication contexts, and cultural and linguistic settings not represented in the evidence base.

(d) Discriminant validity relative to existing frameworks — the degree to which the proposed framework makes contributions that are analytically distinguishable from those of the principal existing models in the field. As documented in Section 7.2, the framework extends the Segel and Heer (2010) narrative visualization spectrum, the S-DIKW framework (Lo Duca & McDowell, 2025), and the three-stage authoring model (Garreton et al., 2025) through the addition of organizational decision-support theory, cognitive load and sensemaking foundations, and explicit evaluation criteria — contributions that are absent from each of those frameworks individually.

The principal limitation of conceptual validation is the absence of empirical evidence regarding the framework's predictive validity — that is, whether organizations that design analytical systems according to its principles demonstrably achieve better decision support outcomes than those that do not. This limitation is acknowledged as a priority direction for future research in Section 13, where experimental and field research designs capable of generating such evidence are identified.

7.4 Criterion-Evidence Mapping

The following table documents the principal theoretical and empirical sources that ground each framework layer and its evaluation criteria, enabling readers to trace the evidential basis of the framework's components and to assess the strength of support for each design principle independently.

Table 2. Criterion-Evidence Mapping: Framework Layers, Evaluation Criteria, and Supporting Literature

Layer	Evaluation Criterion	Primary Evidence Base	Source Tier
1 — Data Foundation	Data quality	(Sánchez-Puchol et al., 2024)	Primary empirical
1 — Data Foundation	Data governance	(Dresner Advisory Services, 2024b)	Tertiary descriptive

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1 — Data Foundation	Ethical data use	(Lo Duca & McDowell, 2025)	Secondary analytical
2 — Analytical Processing	Analytical goal	(Lavalle et al., 2025)	Primary empirical
2 — Analytical Processing	Insight validity	(Shi et al., 2023)	Secondary analytical
2 — Analytical Processing	Interpretive scope	(Sharda et al., 2020)	Secondary analytical
3 — Visual Abstraction	Perceptual accuracy	(Franconeri et al., 2021)	Secondary analytical
3 — Visual Abstraction	Cognitive load optimization	(Sweller et al., 2019; Ware, 2013)	Secondary analytical
3 — Visual Abstraction	Narrative coherence	(Lavalle et al., 2025)	Primary empirical
4 — Narrative Structuring	Structural coherence	(Segel & Heer, 2010; Garreton et al., 2025)	Secondary analytical
4 — Narrative Structuring	Audience calibration	(Shao et al., 2024)	Primary empirical
4 — Narrative Structuring	Narrative integrity	(Hullman & Diakopoulos, 2011; Lo et al., 2022)	Primary empirical
4 — Narrative Structuring	Author-reader balance	(Segel & Heer, 2010)	Secondary analytical
5 — Decision Activation	Actionability	(Dykes, 2019; Sharda et al., 2020)	Secondary analytical
5 — Decision Activation	Uncertainty communication	(Padilla et al., 2025)	Primary empirical
5 — Decision Activation	Decision pathway clarity	(Morrison et al., 2023; Hak et al., 2022)	Primary empirical

Note: source tier follows the classification defined in Section 2.2, Stage 2. Primary empirical sources provide the strongest evidentiary basis; secondary analytical

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sources provide theoretical grounding; tertiary descriptive sources provide contextual support only.

7.5 Boundary Conditions of the Framework

Consistent with the interpretivist-pragmatist epistemological stance articulated in Sections 2.1 and 3.1, the framework's applicability is bounded by a set of organizational and contextual conditions that must be explicitly stated. Applying the framework outside these conditions without adjustment risks generating design recommendations that are technically coherent but organizationally inappropriate (Goldkuhl, 2012; Walsham, 1995).

The framework applies most directly to organizational contexts characterized by the following conditions: structured analytical goals that can be specified in advance of dashboard design; decision-making audiences with identifiable roles, responsibilities, and decision authorities; data environments with sufficient quality and governance to support reliable analytical conclusions; and organizational cultures in which data-driven decision-making is normatively expected rather than episodically adopted. These conditions are broadly characteristic of medium-to-large organizations with established business intelligence functions in sectors such as finance, healthcare administration, retail, manufacturing, and professional services (Sharda et al., 2020; Dresner Advisory Services, 2023).

The framework requires significant adaptation — and may not apply in its current form — under the following conditions. First, in highly exploratory analytical contexts where the decision-maker's questions are themselves unknown or emergent at the time of design, the Narrative Structuring layer's prescriptive design principles may constrain rather than support useful inquiry (Segel & Heer, 2010; Garreton et al., 2025). In such contexts, a reader-driven approach with minimal narrative prescription may better serve the decision-maker's needs, and the framework's evaluation criteria should be adjusted accordingly. Second, in low data literacy environments where decision-makers lack the foundations to engage critically with even narratively structured analytical content, the Decision Activation layer's effectiveness depends on investments in organizational training and data literacy capacity that the framework itself does not address (DataCamp, 2023; Eppler & Mengis, 2004). Third, in public communication contexts — including public health, political communication, and journalism — the rhetorical and ethical dimensions of the Narrative Structuring layer require substantially greater emphasis than in organizational contexts, and the framework's design criteria should be supplemented with audience protection mechanisms suited to heterogeneous and potentially vulnerable public audiences (Schulze et al., 2023; Lo et al., 2022). Fourth, the framework was developed and validated primarily through evidence from English-language literature concentrated in

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North American and European organizational contexts; its applicability to organizational analytics environments in other cultural and linguistic settings — including Latin American, African, and East Asian business cultures with different communicative norms, decision-making hierarchies, and data literacy distributions — requires empirical investigation before confident application (Bahji et al., 2023; Garreton et al., 2025).

7.6 Moderating Variables: A Conceptual Model of Boundary Conditions

The boundary conditions identified in Section 7.5 describe the organizational contexts in which the framework applies, but do not specify the *mechanisms* through which contextual factors amplify or attenuate the effectiveness of data storytelling at each framework layer. This section advances from descriptive boundary conditions to a structured conceptual model of moderating variables — that is, factors whose levels systematically alter the direction or magnitude of the relationship between narrative-oriented analytical design and decision support outcomes (Baron & Kenny, 1986; Aguinis et al., 2016).

Four moderating variables are identified as theoretically central and empirically supported across the literature reviewed in Sections 3 and 4. Each is defined operationally, assigned a theoretical basis, and mapped to the framework layers it most directly affects. The model is summarized in Table 3.

Moderator 1 — Audience Domain Expertise. Domain expertise refers to the decision-maker's prior knowledge of the subject matter represented in the analytical narrative — including familiarity with the relevant metrics, industry context, and causal structures underlying the data (Franconeri et al., 2021; Sweller et al., 2019). This variable moderates the relationship between narrative prescriptiveness and decision quality in two opposing directions. At low levels of expertise, prescriptive narrative structures reduce extraneous cognitive load by supplying the interpretive scaffolding that novice users cannot generate independently — a benefit documented experimentally by Pozdniakov et al. (2023), who found that narrative guidance bridged interpretation gaps most strongly among lower-literacy participants. At high levels of expertise, however, the same prescriptive structures may constrain the expert's capacity for independent analytical exploration, reducing the germane cognitive load that generates deeper comprehension (Sweller et al., 2019; Ruchikachorn & Mueller, 2015). The implication for framework design is directional: Layer 4 (Narrative Structuring) should be more author-driven at low expertise levels and more reader-driven at high expertise levels, with the author-reader balance criterion in Table 2 calibrated accordingly. An expertise threshold below which author-driven structures consistently improve outcomes, and above which reader-driven

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structures are preferable, has not been precisely specified in the experimental literature and constitutes a priority for future empirical research.

Moderator 2 — Cognitive Load at Point of Reception. Cognitive load at point of reception refers to the total processing burden experienced by the decision-maker at the moment of engaging with the analytical narrative — including load imposed by simultaneous task demands, time pressure, organizational stress, and the intrinsic complexity of the decision problem itself, above and beyond the extraneous load imposed by dashboard design (Sweller et al., 2019; Arnold et al., 2023). This variable moderates the effectiveness of narrative structures at Layers 3 and 4: under high ambient cognitive load, even well-designed narrative structures may fail to produce comprehension benefits because the working memory resources required for narrative processing are already exhausted by competing demands (Ke et al., 2023). The operational implication is that the cognitive load optimization criterion (Layer 3) must account not only for the design-generated extraneous load of the visualization but for the total cognitive environment in which the decision-maker operates. Empirical evidence from construction project management dashboards (Ke et al., 2023) suggests that ambient cognitive load above approximately 70% of working memory capacity — indicated behaviorally by elevated fixation counts, increased error rates, and self-reported overload — constitutes a threshold beyond which structural narrative guidance loses its effectiveness and simpler, more minimal displays are preferable regardless of their narrative quality.

Moderator 3 — Visualization Complexity. Visualization complexity refers to the number of visual encoding channels simultaneously active in a display — including color, position, size, shape, and motion — and the degree to which the relationships they represent require multi-step inference to interpret (Franconeri et al., 2021; Ware, 2013). This variable interacts with audience expertise and task type to determine whether narrative structures amplify or suppress comprehension. At low complexity levels, narrative annotation adds value by providing context for otherwise self-evident visual patterns. At moderate complexity, narrative structuring provides its maximum benefit by reducing the inferential work required to connect multiple visual elements into a coherent interpretation — the condition under which Shao et al. (2024) observed the strongest comprehension efficiency gains. At high complexity levels, however, narrative annotations may themselves become additional visual elements competing for attention, and the combined cognitive demand of complex visualization plus narrative annotation may exceed working memory capacity — a phenomenon Franconeri et al. (2021) term *annotation overload*. The operational threshold for this moderator is approximately four to five simultaneous encoding channels, above which narrative annotation should be reduced rather than expanded, and the visual design should be simplified before narrative structuring is applied (Franconeri et al., 2021;

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Ware, 2013). This threshold most directly constrains Layer 3 (Visual Abstraction) and has upstream implications for Layer 2 (Analytical Processing): analytical outputs that cannot be represented within four to five encoding channels should be decomposed into multiple sequential narrative frames rather than a single complex display.

Moderator 4 — Decision Task Type and Urgency. Decision task type refers to the cognitive demands imposed by the decision itself — specifically the distinction between *retrieval tasks* (locating a specific value or fact within a display), *single-insight comprehension tasks* (understanding the meaning and implication of one pattern), and *multi-insight integration tasks* (synthesizing multiple patterns into a strategic conclusion) (Shao et al., 2024; Dimara & Stasko, 2022). This variable is the most consequential moderator identified in the recent experimental literature: Shao et al. (2024) found that data storytelling significantly improved efficiency and accuracy for retrieval and single-insight tasks, but produced no significant benefit for multi-insight integration tasks — a finding that directly challenges the common practitioner claim that narrative-structured dashboards universally improve decision quality. Decision urgency — the time pressure under which the decision must be made — interacts with task type to further constrain narrative effectiveness: under high urgency, even well-designed narrative sequences may be bypassed by decision-makers who scan for conclusions rather than following the intended narrative path (Kahneman, 2011; Morrison et al., 2023). The combined implication for Layer 5 (Decision Activation) is that actionability mechanisms must be designed differently depending on task type and urgency: for retrieval and single-insight tasks under moderate urgency, author-driven narrative with explicit insight-first structuring is appropriate; for multi-insight integration tasks or high-urgency decisions, the narrative should be condensed to a summary conclusion with optional drill-down rather than a sequential analytical story.

Table 3. Conceptual Model of Moderating Variables: Definitions, Theoretical Basis, Directional Effects, and Framework Layer Impacts

Moderating Variable	Operational Definition	Theoretical Basis	Direction of Effect	Primary Framework Layer Affected
Audience domain expertise	Prior knowledge of subject matter, metrics, and causal structures	CLT (Sweller et al., 2019); Situated Cognition (Elsbach et al., 2005)	Low expertise → author-driven narrative benefits; High expertise → reader-driven	Layer 4 (Narrative Structuring)

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			preferred	
Cognitive load at reception	Total processing burden at moment of engagement, including ambient task demands and time pressure	CLT (Sweller et al., 2019); Ke et al. (2023)	Below ~70% WM capacity → narrative benefits hold; Above threshold → minimal display preferred	Layers 3–4 (Visual Abstraction, Narrative Structuring)
Visualization complexity	Number of simultaneous encoding channels and inferential steps required	Franconeri et al. (2021); Ware (2013)	≤4–5 channels → narrative annotation beneficial; >5 channels → annotation overload risk	Layers 2–3 (Analytical Processing, Visual Abstraction)
Decision task type and urgency	Retrieval vs. single-insight vs. multi-insight integration; time pressure	Shao et al. (2024); Dimara & Stasko (2022)	Single-insight tasks → strong narrative benefit; Multi-insight tasks → no consistent benefit; High urgency → conclusion-first design required	Layer 5 (Decision Activation)

Note: CLT = Cognitive Load Theory; WM = working memory. Threshold values are indicative rather than precisely established; empirical calibration across organizational contexts is required before these thresholds can be treated as design specifications.

The moderating variable model advances the framework beyond the descriptive boundary conditions of Section 7.5 in three respects. First, it specifies *mechanisms* — the theoretical pathways through which contextual factors alter outcomes — rather than simply listing contexts where the framework does or does not apply. Second, it assigns *directional predictions* — stating not only that expertise moderates effectiveness but in which direction and at which approximate threshold. Third, it provides *layer-specific implications* — connecting each moderating variable to the

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specific design decisions within the framework where its influence is strongest, enabling practitioners to calibrate their design choices to their organizational context rather than applying the framework's principles uniformly. The absence of precise empirically calibrated thresholds for most moderators is acknowledged as a limitation, and the experimental investigation of these thresholds across diverse organizational settings is identified as a priority for future research in Section 13.

8. Tools and Technologies for Data Storytelling

The implementation of data storytelling in organizational contexts depends on technological infrastructures capable of integrating data processing, visualization, and communication of analytical insights. Modern analytics ecosystems combine business intelligence platforms, visualization libraries, and artificial intelligence tools that enable the creation of interactive dashboards and narrative data presentations. These technologies allow analysts to transform large datasets into interpretable visual structures that support decision-making processes (Sharda, Delen, & Turban, 2020; Chen, Chiang, & Storey, 2012).

Recent advances in analytics technologies have expanded the capabilities of visualization platforms by incorporating features such as interactive dashboards, natural language queries, automated insight generation, and collaborative data exploration environments. These developments enable organizations to communicate complex analytical insights more effectively and reduce the cognitive barriers associated with interpreting large volumes of data (Davenport & Harris, 2007; Heer, Bostock, & Ogievetsky, 2010).

The following sections examine the main categories of tools that support the implementation of data storytelling in modern analytics environments.

8.1 Business Intelligence Platforms

Business intelligence platforms represent one of the most widely used technological infrastructures for implementing data storytelling practices in organizations. These systems integrate data collection, processing, visualization, and reporting functionalities, allowing analysts to create dashboards that communicate insights through structured visual narratives (Sharda et al., 2020).

Among the most widely adopted BI platforms are **Microsoft Power BI**, **Tableau**, **Looker**, and **Apache Superset**. These systems provide advanced visualization

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capabilities and dashboard development environments that support the creation of narrative-oriented analytical reports.

For example, **Microsoft Power BI** enables analysts to build interactive dashboards that combine multiple visual components such as charts, tables, filters, and key performance indicators (KPIs). The platform also integrates natural language query capabilities through its Q&A feature, allowing users to retrieve analytical insights by asking questions in natural language. This functionality helps reduce technical barriers to analytics and enables broader organizational access to data-driven insights (Sharda et al., 2020).

Similarly, **Tableau** is widely recognized for its powerful visualization capabilities and its support for narrative dashboards. The platform allows analysts to organize visualizations into sequential "stories," which guide users through a structured analytical narrative. These storytelling features enable analysts to contextualize data patterns and highlight key insights within dashboards (Knaflic, 2015; Few, 2013).

Another important analytics platform is **Looker**, which emphasizes semantic data modeling and centralized metric definitions. By defining business metrics within a semantic modeling layer, Looker allows organizations to maintain consistency in analytical interpretations across departments and dashboards, which is particularly important for narrative communication of organizational performance metrics (Chen et al., 2012).

Open-source platforms such as **Apache Superset** are also increasingly adopted in analytics infrastructures. Superset provides interactive visualization and dashboard capabilities while allowing integration with modern data pipelines and distributed data systems. Because it is open-source, Superset can be integrated with other analytical tools and programming environments, enabling flexible development of customized storytelling dashboards (Sharda et al., 2020).

Together, these BI platforms provide the technological foundation that enables organizations to transform raw data into interactive analytical narratives.

8.2 Interactive Visualization Tools

Interactive visualization technologies play a central role in data storytelling because they enable users to explore datasets dynamically and identify patterns through exploratory analysis. Unlike static visualizations, interactive dashboards allow users to manipulate visual representations of data by applying filters, selecting variables, and exploring multiple analytical dimensions (Few, 2013).

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One important capability of interactive visualization systems is **drill-down analysis**, which allows users to progressively navigate through different levels of data granularity. For instance, an analyst may begin by examining aggregated sales performance at a regional level and then drill down into country-level or product-level data to identify the underlying factors that influence performance trends (Shneiderman, 1996).

Interactive features are widely supported by modern BI platforms such as Tableau and Power BI. These platforms allow analysts to build dashboards that respond dynamically to user interaction through mechanisms such as filters, linked visualizations, hover-based annotations, and dynamic highlighting of data elements.

In addition to commercial BI platforms, **programming-based visualization libraries** have become increasingly important for building customized data storytelling applications. Programming environments such as **Python** and **JavaScript** provide libraries that allow analysts to design interactive visualizations tailored to specific analytical tasks.

For example, **Python visualization libraries** such as **Matplotlib**, **Seaborn**, **Plotly**, and **Altair** enable analysts to create a wide variety of charts and interactive visualizations for exploratory analysis and reporting. These libraries are frequently used in data science workflows because they allow analysts to integrate visualization directly with data processing and machine learning pipelines (Hunter, 2007; VanderPlas, 2016).

More advanced frameworks such as **Plotly Dash** and **Streamlit** allow developers to build full interactive analytical applications that combine data processing, visualization, and narrative explanations within web-based interfaces. These technologies enable the development of customized storytelling dashboards that go beyond the capabilities of traditional BI tools (Heer et al., 2010).

Through these technologies, interactive visualization becomes an important mechanism for supporting the exploratory and narrative dimensions of data storytelling.

8.3 Data Storytelling Platforms

In addition to traditional BI tools, several platforms have been developed specifically to support narrative data communication. These tools integrate visualizations with textual explanations, annotations, and structured narrative flows that guide users through analytical insights.

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Platforms such as **Flourish**, **Datawrapper**, and **Observable** are widely used in data journalism and analytical reporting contexts. These platforms allow analysts to combine interactive visualizations with narrative explanations that contextualize data patterns and guide readers through analytical stories (Segel & Heer, 2010).

A common technique supported by these storytelling platforms is **scrollytelling**, in which users navigate through a sequence of visualizations and narrative explanations while scrolling through a webpage. This approach allows analysts to progressively reveal insights and maintain user engagement throughout the analytical narrative.

Narrative features are also increasingly integrated into traditional BI systems. For example, Tableau dashboards can include annotations, captions, and explanatory text that highlight key insights within visualizations. These narrative components help users interpret the significance of patterns in the data and facilitate more effective communication of analytical results (Knaflic, 2015).

These developments demonstrate how storytelling principles are increasingly embedded within modern analytical technologies.

8.4 AI-Assisted Analytics

Artificial intelligence technologies are increasingly integrated into analytics platforms to support automated insight discovery and narrative explanation of data patterns. AI-assisted analytics systems use machine learning algorithms to detect patterns, anomalies, and correlations in datasets and generate explanations that help users interpret analytical results (Davenport & Bean, 2018).

Many modern BI platforms now incorporate **AI-powered analytical assistants**, sometimes referred to as **analytics copilots**. These systems analyze datasets and dashboards to automatically highlight significant trends, identify anomalies, and generate textual summaries that describe the insights discovered in the data.

For example, **Microsoft Power BI** includes AI features that automatically generate insights from datasets, identify correlations between variables, and provide explanations of visual patterns within dashboards. Similarly, **Tableau AI** integrates machine learning capabilities that support automated data analysis and natural language explanations of analytical results (Sharda et al., 2020).

AI-assisted analytics systems also enable **natural language interaction with data**. Users can ask questions about datasets using conversational queries, and the system automatically generates relevant visualizations and explanations. These natural language interfaces significantly lower the barrier to accessing analytics by

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allowing non-technical users to explore data without requiring knowledge of query languages or analytical tools (Chen et al., 2012).

As artificial intelligence technologies continue to evolve, analytics platforms are expected to incorporate increasingly advanced capabilities for automated insight discovery and narrative generation. These developments will likely play a central role in the future evolution of data storytelling and analytics-driven decision-making.

10. Organizational Applications

The practical value of data storytelling becomes particularly evident in organizational contexts, where analytical insights must be translated into actionable knowledge for decision-makers. While traditional analytical reporting often focuses on presenting quantitative indicators, storytelling-oriented approaches emphasize contextual interpretation, narrative explanation, and the communication of strategic implications derived from data (Davenport & Harris, 2007; Sharda, Delen, & Turban, 2018).

In data-intensive organizations, decision-makers frequently face the challenge of interpreting large volumes of analytical outputs produced by business intelligence and analytics systems. Without proper contextualization, these analytical outputs may fail to influence strategic or operational decisions. Data storytelling is proposed as a response to this limitation, with the design premise that structuring analytical findings into coherent narratives may highlight relevant patterns, support the communication of causal relationships, and help clarify their implications for organizational objectives — effects that are plausible on cognitive-theoretical grounds and partially supported by experimental evidence, but whose organizational magnitude depends on data literacy, narrative quality, and decision context (Shao et al., 2024; Sánchez-Puchol et al., 2024; Concannon et al., 2023).

From an organizational perspective, storytelling with data functions as a communication mechanism that reduces the gap between technical analytics teams and managerial stakeholders. By integrating visualization, narrative structure, and contextual explanation, storytelling frameworks enable organizations to transform analytical results into insights that support decision-making across different functional domains, including strategy, marketing, finance, and operations (Davenport & Harris, 2007; Sharda et al., 2018).

10.1 Strategic Decision-Making

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Strategic decision-making represents one of the most important contexts in which data storytelling can enhance organizational performance. Strategic decisions typically involve complex trade-offs, long-term uncertainty, and multiple performance indicators, making it difficult for decision-makers to interpret purely numerical analytical outputs (Davenport & Harris, 2007).

Data storytelling contributes to strategic decision-making by organizing analytical information into narratives that emphasize trends, causal relationships, and strategic implications. Through narrative dashboards and structured visual explanations, storytelling techniques help executives understand not only what the data indicates but also why it matters for organizational strategy (Sharda et al., 2018).

Furthermore, storytelling approaches allow analytical insights to be framed within broader strategic contexts, such as market dynamics, competitive positioning, and operational capabilities. This contextualization improves executives' ability to evaluate alternative strategic options and prioritize organizational initiatives based on data-driven insights (Provost & Fawcett, 2013).

By structuring complex analytical results within interpretable narratives, data storytelling may reduce the cognitive distance between analytics and executive decision-making — a theoretically grounded claim supported by evidence on cognitive load reduction (Sweller et al., 2019) and comprehension efficiency (Shao et al., 2024), though empirical evidence specifically testing this effect in strategic executive decision contexts remains limited (Concannon et al., 2023).

10.1.1 Strategic KPI Interpretation

Key Performance Indicators (KPIs) play a central role in strategic management by providing measurable representations of organizational objectives and performance outcomes. However, the interpretation of KPIs often requires contextual understanding of organizational processes, external market conditions, and relationships among multiple indicators (Sharda et al., 2018).

Data storytelling enhances KPI interpretation by embedding performance metrics within explanatory narratives that clarify their strategic significance. Rather than presenting isolated numerical indicators, narrative dashboards organize metrics into coherent analytical structures that highlight patterns, trends, and underlying drivers of performance outcomes (Provost & Fawcett, 2013).

In addition, storytelling techniques help organizations prioritize metrics by identifying which indicators are most relevant to specific strategic objectives. Since modern organizations often track large numbers of performance metrics, narrative-based

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analytics can guide executive attention toward the indicators that require immediate strategic intervention (Davenport & Harris, 2007).

By contextualizing metrics within narrative explanations, data storytelling transforms KPI dashboards into tools for strategic interpretation rather than simple monitoring systems.

10.1.2 Scenario-Based Analytical Narratives

Scenario-based analysis represents another important application of data storytelling in strategic decision-making environments. Organizations frequently rely on predictive analytics and forecasting models to evaluate alternative future outcomes under different market conditions or operational assumptions (Provost & Fawcett, 2013).

Data storytelling facilitates the communication of predictive insights by structuring analytical outputs into scenario-based narratives. Instead of presenting predictive models as isolated statistical outputs, storytelling techniques guide decision-makers through the assumptions, data patterns, and potential consequences associated with each scenario (Sharda et al., 2018).

Narrative dashboards may present multiple alternative scenarios—such as optimistic, moderate, and pessimistic projections—while explaining the underlying drivers that influence each projection. This approach helps executives better understand the uncertainty inherent in predictive analytics and evaluate potential strategic responses (Davenport & Harris, 2007).

Furthermore, visual representations of scenario projections, such as trend graphs and comparative simulations, enhance executives' ability to interpret future trajectories and identify emerging strategic opportunities or risks.

10.1.3 Executive Communication of Insights

One of the primary challenges in data-driven organizations involves the communication of analytical insights to executive leadership. Analytical outputs generated by data scientists and analysts often involve complex statistical models, which may be difficult for non-technical decision-makers to interpret directly (Provost & Fawcett, 2013).

Data storytelling addresses this challenge by translating complex analytical findings into clear narratives supported by visual representations. By integrating charts, annotations, and explanatory text, storytelling approaches enable analysts to

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communicate insights in ways that are accessible to executive audiences (Knaflic, 2015).

Narrative communication also improves the persuasive impact of analytical findings. Structured narratives typically present insights through logical sequences—such as problem identification, analytical investigation, and recommended actions—making it easier for executives to understand the implications of the analysis (Davenport & Harris, 2007).

As a result, storytelling techniques contribute not only to analytical interpretation but also to organizational alignment, ensuring that analytical insights effectively inform executive decision-making processes.

10.2 Marketing Analytics

Marketing analytics represents another domain in which data storytelling plays a critical role. Modern marketing environments generate large volumes of behavioral data derived from digital interactions, social media activity, and customer engagement across multiple channels (Wedel & Kannan, 2016).

While analytical tools can identify patterns within these datasets, effective decision-making requires the ability to interpret customer behavior in meaningful ways. Data storytelling provides mechanisms for organizing behavioral data into narratives that explain how customers interact with products, services, and marketing campaigns (Davenport, 2014).

By integrating visualization and narrative explanation, storytelling techniques help marketing analysts communicate insights about customer preferences, campaign effectiveness, and market trends. These insights support the design of more effective marketing strategies and customer engagement initiatives (Wedel & Kannan, 2016).

9.2.1 Customer Behavior Narratives

Understanding customer behavior represents a central objective of marketing analytics. Behavioral datasets often include information about customer interactions, purchasing patterns, browsing activity, and engagement with marketing content (Wedel & Kannan, 2016).

Data storytelling enables analysts to interpret these datasets by constructing narratives that explain the sequence of customer interactions across multiple touchpoints. Visualizations such as customer journey maps and behavioral flow

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diagrams allow organizations to understand how customers move through different stages of the purchasing process (Davenport, 2014).

Narrative representations of customer behavior also help organizations identify critical moments within the customer journey, such as points of engagement, friction, or abandonment. By highlighting these patterns, storytelling techniques support the development of more effective marketing strategies and personalized customer experiences.

10.2.2 Campaign Performance Storytelling

Marketing campaigns generate large quantities of performance data, including metrics related to impressions, conversions, engagement rates, and customer acquisition costs. However, interpreting these metrics requires contextual analysis that explains how campaign performance evolves over time (Wedel & Kannan, 2016).

Data storytelling enables marketing teams to communicate campaign performance through narrative dashboards that illustrate key trends and explain the factors influencing campaign outcomes. Visualizations may highlight variations in engagement across different customer segments, communication channels, or time periods (Davenport, 2014).

By structuring campaign metrics within narrative explanations, storytelling techniques allow organizations to identify actionable insights that inform future marketing initiatives.

10.2.3 Market Trend Communication

In addition to campaign analysis, marketing analytics also involves the identification and communication of broader market trends. Market data may include information about competitor activity, consumer preferences, and macroeconomic influences affecting demand (Wedel & Kannan, 2016).

Data storytelling helps analysts communicate these trends by organizing market indicators into narratives that explain how industry dynamics evolve over time. Visualizations of market share changes, competitive positioning, and emerging consumer behaviors enable decision-makers to interpret complex market environments more effectively (Davenport, 2014).

Through narrative communication, organizations can translate market analytics into strategic insights that guide product development, pricing strategies, and competitive positioning.

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10.3 Financial Analytics

Financial analytics represents another domain where data storytelling can enhance the interpretation of complex datasets. Financial indicators such as revenue growth, profitability, liquidity, and cost structures often require contextual interpretation in order to support strategic financial decision-making (Few, 2013).

Data storytelling techniques help organizations interpret financial indicators by embedding metrics within explanatory narratives that clarify the drivers of financial performance. Through the use of visual dashboards and narrative annotations, analysts can explain how operational, market, and strategic factors influence financial outcomes (Knaflic, 2015).

By transforming financial data into interpretable narratives, storytelling techniques enable financial leaders to communicate performance insights more effectively across organizational levels.

10.3.1 Financial Performance Narratives

Financial performance narratives integrate multiple financial indicators into coherent explanations of organizational results. Instead of presenting isolated financial metrics, storytelling approaches contextualize performance outcomes within broader business dynamics (Few, 2013).

For example, variations in profitability may be explained through narratives that combine information about sales performance, operational costs, and market conditions. Visual dashboards that illustrate these relationships help executives understand the underlying drivers of financial outcomes (Knaflic, 2015).

Such narrative interpretations are particularly valuable during financial reviews and strategic planning processes, where decision-makers must evaluate the sustainability of financial performance.

10.3.2 Risk Communication Through Data Visualization

Risk communication represents a critical component of financial analytics. Financial risks often involve probabilistic scenarios, uncertainty, and complex interactions among economic variables, making them difficult to interpret using purely numerical representations (Few, 2013).

Data storytelling enables organizations to communicate financial risks through visual narratives that illustrate potential scenarios and their implications. For example,

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scenario visualizations may demonstrate how changes in market conditions could influence revenue projections or cost structures (Knaflic, 2015).

By presenting risk information through structured visual narratives, storytelling techniques improve the ability of executives to evaluate uncertainty and make informed financial decisions.

10.3.3 Executive Financial Dashboards

Executive financial dashboards represent an important interface between financial analytics and leadership decision-making. These dashboards typically present key financial indicators such as revenue growth, cost efficiency, and profitability metrics (Few, 2013).

When designed according to storytelling principles, executive dashboards go beyond simple metric presentation by highlighting patterns, anomalies, and strategic implications within financial data. Narrative annotations and contextual explanations guide executives through the interpretation of financial performance indicators (Knaflic, 2015).

As a result, storytelling-oriented financial dashboards support more effective financial governance by enabling leaders to identify critical issues and prioritize strategic financial actions.

10.4 Operational Analytics

Operational analytics focuses on improving the efficiency and effectiveness of organizational processes. In operational environments such as manufacturing, logistics, and service operations, large volumes of process data are generated through information systems and digital monitoring technologies (Sharda et al., 2018).

Data storytelling enhances operational analytics by transforming process metrics into narratives that explain how operational systems function and where inefficiencies occur. Through narrative dashboards and explanatory visualizations, organizations can communicate insights about process performance and operational bottlenecks (Davenport & Harris, 2007).

These insights support continuous improvement initiatives and operational decision-making across multiple organizational functions.

10.4.1 Process Monitoring Narratives

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Process monitoring systems collect data about operational performance, including metrics related to production efficiency, service delivery times, and resource utilization. However, interpreting these metrics requires contextual understanding of how different process components interact (Sharda et al., 2018).

Data storytelling enables analysts to construct narratives that explain process dynamics by combining visualizations of performance indicators with contextual explanations. These narratives help managers identify patterns, detect anomalies, and understand the causes of operational inefficiencies.

10.4.2 Supply Chain Analytics Storytelling

Supply chain analytics involves analyzing complex networks of suppliers, logistics processes, and distribution systems. These systems generate large volumes of data related to inventory levels, transportation flows, and supplier performance (Davenport & Harris, 2007).

Data storytelling helps organizations interpret supply chain data by structuring logistics metrics into narratives that explain operational relationships across the supply chain. Visual dashboards may illustrate how disruptions in one part of the supply chain affect downstream operations.

By communicating supply chain insights through narrative structures, organizations can improve coordination and responsiveness within their logistics networks.

10.4.3 Performance Improvement Insights

One of the ultimate goals of operational analytics is the identification of opportunities for performance improvement. Data storytelling supports this objective by transforming operational data into actionable insights that highlight inefficiencies, bottlenecks, and optimization opportunities (Sharda et al., 2018).

Narrative dashboards that combine performance metrics with explanatory annotations allow managers to understand not only where performance problems occur but also why they occur and how they can be addressed.

Through this approach, data storytelling contributes to continuous improvement initiatives by enabling organizations to communicate operational insights clearly and effectively across different organizational levels.

11. Challenges and Implementation Barriers

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Beyond the implementation barriers examined in this section, it is important to acknowledge that the empirical evidence base for data storytelling's effectiveness is more contested than practitioner-oriented literature typically suggests. Three findings from the controlled experimental literature warrant explicit recognition. First, the systematic review by Concannon et al. (2023) found that evaluation in the narrative visualization field relies predominantly on informal practitioner judgment, and that no standardized evaluation framework exists — meaning that many effectiveness claims in the literature reflect expert opinion rather than controlled evidence. Second, the experimental study by Shao et al. (2024) found no significant benefit of data storytelling for multi-insight comprehension tasks, suggesting that prescriptive narrative structures may constrain the integrative analysis required for complex strategic decisions. Third, the experimental findings of Braga and Silva (2021) and the systematic analysis of Shi et al. (2023) document that narrative structuring consistently introduces framing effects that audiences are unable to detect — meaning that data storytelling's potential to improve comprehension may be inseparable from its potential to bias judgment. These findings do not negate the conditional value of data storytelling, but they establish that its benefits are bounded, context-dependent, and accompanied by interpretive risks that responsible organizational deployment must explicitly manage.

Although data storytelling has gained increasing attention as a mechanism for improving the interpretability of analytics, its implementation in organizational environments presents several practical and theoretical challenges. Organizations attempting to integrate narrative-based analytics into decision-making processes frequently encounter barriers related to analytical competencies, organizational culture, technological infrastructure, and ethical risks associated with persuasive communication (Chen, Chiang, & Storey, 2012; Davenport & Harris, 2007; Hullman & Diakopoulos, 2011).

In many organizations, the transition toward data-driven decision-making requires not only the adoption of analytical technologies but also the development of analytical capabilities among employees and managers. Research on business analytics adoption suggests that the effectiveness of analytics initiatives depends heavily on the ability of organizational stakeholders to interpret analytical outputs and integrate them into decision-making processes (Davenport & Harris, 2007; Brynjolfsson & McElheran, 2016).

Furthermore, storytelling approaches introduce additional interpretative dimensions into analytical communication. While narrative visualization can enhance comprehension and engagement, it may also influence how audiences interpret analytical results. Consequently, scholars emphasize the importance of

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understanding the potential biases and limitations associated with narrative-based data communication (Hullman & Diakopoulos, 2011; Segel & Heer, 2010).

11.1 Data Literacy Gap

One of the most widely discussed barriers to the effective adoption of data storytelling is the **data literacy gap** within organizations. Data literacy refers to the ability of individuals to read, interpret, and critically evaluate data and analytical outputs in order to support decision-making processes (Davenport & Harris, 2007).

Studies indicate that many organizations struggle to fully leverage analytics because employees lack the analytical competencies required to interpret complex datasets and visualizations. As a result, analytical insights generated by data systems may remain underutilized or misunderstood by decision-makers (Chen et al., 2012; Davenport & Harris, 2007).

Industry research has also highlighted that insufficient data literacy represents a major barrier to becoming a data-driven organization. Without adequate analytical skills, employees may struggle to interpret dashboards, evaluate analytical evidence, or recognize the strategic implications of data-driven insights (Gartner, 2021).

11.1.1 Analytical Skills Deficit

A central component of the data literacy gap involves the **deficit of analytical skills** among organizational stakeholders. Analytical decision-making requires familiarity with concepts such as statistical relationships, data distributions, uncertainty, and trend interpretation. However, many employees and managers lack formal training in these analytical concepts (Davenport & Harris, 2007).

This limitation can significantly affect the effectiveness of storytelling-based analytics. Even when analytical results are presented through simplified visual narratives, decision-makers must still understand the underlying patterns represented in the data. Without sufficient analytical competencies, users may misinterpret analytical insights or fail to recognize their significance for organizational strategy (Chen et al., 2012).

Consequently, the lack of analytical skills can limit the impact of storytelling dashboards and reduce the effectiveness of analytics initiatives in supporting evidence-based decision-making.

11.1.2 Data Interpretation Barriers

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In addition to general analytical skills deficits, many organizational users encounter difficulties interpreting graphical representations of data. Visualization techniques such as scatter plots, multi-dimensional dashboards, and predictive trend visualizations often require familiarity with graphical conventions and analytical reasoning (Ware, 2013; Chen et al., 2012).

Research in information visualization has demonstrated that users may misinterpret visual representations when they are unfamiliar with graphical encoding methods, scale manipulation, or multi-variable visualizations. These interpretation challenges can limit the effectiveness of dashboards and narrative visualizations intended to support decision-making (Ware, 2013).

Consequently, the success of storytelling-based analytics depends not only on the design of visualizations but also on the ability of users to interpret graphical information correctly.

11.1.3 Organizational Training Needs

To address the data literacy gap, many organizations have begun investing in **data literacy training programs** aimed at improving employees' analytical competencies. These initiatives typically focus on developing skills related to data interpretation, statistical reasoning, and the effective use of visualization tools (Gartner, 2021).

Research on analytics adoption suggests that organizations that invest in analytical education are more likely to successfully integrate analytics into decision-making processes. Training initiatives can improve employees' confidence in interpreting analytical insights and enhance their ability to engage with storytelling-based dashboards (Davenport & Harris, 2007).

As a result, the development of analytical competencies is increasingly recognized as a critical factor in the successful implementation of data storytelling initiatives.

11.2 Organizational Resistance

Beyond analytical competencies, the adoption of data storytelling also depends on organizational culture. Research on analytics adoption has shown that many organizations encounter resistance when attempting to transition toward data-driven decision-making practices (Brynjolfsson & McElheran, 2016).

In environments where decision-making has historically relied on managerial intuition or experience, the introduction of analytical evidence may challenge established decision-making norms. As a result, employees and managers may resist adopting

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analytical systems or narrative dashboards that alter traditional decision processes (Davenport, 2014).

Organizational resistance can therefore represent a significant barrier to the successful implementation of storytelling-based analytics.

11.2.1 Cultural Barriers to Data-Driven Decision-Making

Organizational culture strongly influences the extent to which data-driven insights are incorporated into managerial decisions. Studies on analytics adoption suggest that organizations characterized by hierarchical decision-making or intuition-based management may demonstrate lower levels of analytical integration (Brynjolfsson & McElheran, 2016).

In such environments, analytical evidence may be perceived as secondary to managerial experience or organizational tradition. This cultural resistance can reduce the influence of data storytelling dashboards on decision-making processes, even when analytical insights are clearly presented (Davenport, 2014).

Developing a data-driven culture therefore requires not only technological investment but also organizational commitment to evidence-based decision-making practices.

11.2.2 Organizational Change Management

The implementation of data storytelling often requires significant organizational change. The integration of analytics into decision-making processes may alter workflows, redefine responsibilities, and introduce new analytical roles within organizations (Davenport & Harris, 2007).

Effective change management strategies are therefore necessary to facilitate the adoption of analytics systems. These strategies may include the development of governance frameworks for analytics initiatives, the establishment of cross-functional analytics teams, and the promotion of collaborative decision-making practices (Brynjolfsson & McElheran, 2016).

Without appropriate change management mechanisms, organizations may struggle to integrate storytelling-based analytics into everyday decision-making processes.

11.2.3 Leadership and Analytics Adoption

Leadership plays a critical role in shaping the adoption of analytics within organizations. Research has shown that executive support for data-driven decision-making significantly influences the success of analytics initiatives (Davenport, 2014).

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When organizational leaders actively promote the use of analytical insights, they create incentives for employees to adopt analytical tools and engage with data-driven decision processes. Conversely, when leadership relies primarily on intuition or experience, analytics initiatives may fail to gain organizational legitimacy (Davenport & Harris, 2007).

Thus, leadership commitment is widely recognized as a key factor in fostering the adoption of data storytelling practices within organizations.

11.3 Technical Constraints

In addition to cultural and organizational challenges, the implementation of data storytelling may also be constrained by technological limitations. Analytical dashboards and storytelling platforms rely on robust data infrastructures capable of integrating large volumes of data from multiple organizational systems (Chen et al., 2012).

If data infrastructures are fragmented or poorly integrated, organizations may encounter difficulties producing reliable analytical insights. These technological constraints can reduce the effectiveness of storytelling dashboards and undermine trust in analytical outputs.

11.3.1 Data Integration Problems

One common technical challenge in analytics environments involves the integration of heterogeneous data sources. Organizations often maintain separate information systems for different functional areas, such as finance, marketing, operations, and customer relationship management (Chen et al., 2012).

Integrating these systems into unified analytical platforms may require significant effort due to inconsistencies in data formats, data quality issues, and incompatible system architectures. Such integration challenges can limit the ability of organizations to develop comprehensive storytelling dashboards that combine insights from multiple data sources.

11.3.2 Infrastructure Limitations

The effectiveness of storytelling-based analytics also depends on the availability of appropriate analytical infrastructure. Large-scale analytics initiatives require scalable storage systems, data processing capabilities, and visualization tools capable of handling complex datasets (Chen et al., 2012).

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Organizations with limited technological infrastructure may experience difficulties processing large datasets or generating interactive dashboards. These limitations can affect the responsiveness and usability of storytelling platforms, reducing their value for decision-makers.

11.3.3 Visualization Tool Limitations

Although modern business intelligence platforms provide powerful visualization capabilities, they may also impose constraints on dashboard design and narrative communication. Some visualization tools limit customization options or restrict the representation of complex analytical relationships (Chen et al., 2012).

Such limitations may hinder analysts' ability to design visual narratives that effectively communicate analytical insights. As a result, the effectiveness of data storytelling may depend on the careful selection and configuration of visualization tools.

11.4 Narrative Bias Risks

While storytelling techniques can improve the interpretability of analytical insights, they also introduce potential risks related to **narrative bias**. Narrative visualizations involve interpretative framing, which may influence how audiences perceive data and analytical results (Hullman & Diakopoulos, 2011).

Researchers in visualization studies have emphasized that storytelling techniques can shape audience interpretation by emphasizing specific data patterns or framing analytical results within particular narratives (Segel & Heer, 2010). Consequently, narrative-based analytics must be applied carefully to avoid misleading interpretations.

11.4.1 Persuasive Visualization

Visualizations are inherently rhetorical because design choices such as color, scale, and emphasis can influence how viewers interpret data. Narrative visualization often uses these design elements to guide audience attention toward specific insights or interpretations (Hullman & Diakopoulos, 2011).

Although persuasive visualization can enhance communication, it may also introduce bias if visual elements exaggerate particular patterns or obscure uncertainty within the data.

11.4.2 Analytical Manipulation Risks

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Another risk associated with narrative analytics involves the selective presentation of data. Analysts may unintentionally—or deliberately—select specific variables, time periods, or datasets that support a particular narrative while excluding contradictory evidence (Hullman & Diakopoulos, 2011).

Such selective presentation can distort analytical interpretation and lead to misleading conclusions. Transparency in data sources and analytical methods is therefore essential for maintaining the credibility of storytelling-based analytics.

11.4.3 Ethical Considerations in Data Storytelling

Ethical considerations represent an important dimension of data storytelling practices. Because narrative visualizations may influence decision-making, analysts must ensure that data is communicated accurately and responsibly (Hullman & Diakopoulos, 2011).

Ethical storytelling requires avoiding misleading visualizations, clearly communicating uncertainty, and acknowledging the limitations of analytical models. By adhering to these principles, organizations can ensure that storytelling techniques support responsible and transparent data communication.

12. Future Directions

The evolution of analytics technologies and visualization tools continues to transform how organizations interpret and communicate data-driven insights. In recent years, emerging technologies such as artificial intelligence, conversational analytics, and decision intelligence systems have significantly expanded the capabilities of data storytelling frameworks. These developments are enabling more automated, interactive, and context-aware analytical narratives, which can support decision-making across organizational levels. As organizations increasingly rely on data-driven strategies, the integration of intelligent analytical systems and natural language interfaces is expected to reshape how analytical insights are generated, interpreted, and communicated (Davenport & Bean, 2018; Sharda, Delen, & Turban, 2020).

This section discusses emerging directions that are likely to influence the future of data storytelling and analytics-driven communication in organizations.

12.1 AI-Generated Analytical Narratives

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One of the most promising developments in the analytics landscape is the use of artificial intelligence to automatically generate analytical narratives. AI-driven systems are increasingly capable of transforming structured datasets into textual explanations that highlight patterns, trends, and anomalies. This process, often referred to as automated narrative generation, allows analytical platforms to produce contextual explanations that complement visual dashboards (Davenport & Bean, 2018).

Natural language generation (NLG) technologies play a central role in this process. By converting quantitative information into narrative descriptions, NLG systems enable organizations to communicate insights in a format that is more accessible to non-technical stakeholders. These capabilities reduce the gap between data analysis and business understanding, allowing decision-makers to interpret complex analytical outputs without requiring advanced statistical knowledge (Gartner, 2021).

Furthermore, AI-generated narratives can support continuous monitoring of organizational metrics by automatically detecting relevant changes in data streams and generating explanatory insights. As analytics platforms evolve, these capabilities are expected to become increasingly integrated into business intelligence environments, enabling real-time narrative reporting and automated insight generation (Davenport & Bean, 2018).

12.1.1 Automated Insight Generation

Automated insight generation refers to the ability of analytical systems to identify significant patterns within large datasets without requiring manual exploration. Machine learning algorithms can detect correlations, trends, and anomalies that may otherwise remain unnoticed by analysts. These systems can then translate these findings into structured insights, which can be incorporated into narrative dashboards (Sharda et al., 2020).

12.1.2 Natural Language Analytics

Natural language analytics allows users to interact with data through human language queries rather than traditional query languages or manual dashboard exploration. This capability improves accessibility by enabling users with limited technical expertise to retrieve insights through simple questions expressed in natural language (Gartner, 2021).

12.1.3 AI-Assisted Dashboard Interpretation

AI-assisted dashboards combine visualization tools with machine learning algorithms capable of generating explanatory annotations. These annotations help users

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understand why certain patterns appear in the data, providing contextual explanations that enhance the interpretability of dashboards and support more informed decision-making (Davenport & Bean, 2018).

12.2 Conversational Analytics

Conversational analytics represents another important direction in the evolution of data storytelling. This approach allows users to interact with analytical systems using natural language interfaces, enabling more intuitive exploration of datasets. Instead of manually configuring dashboards or writing structured queries, users can ask questions about their data and receive immediate analytical responses (Sharda et al., 2020).

Conversational interfaces can also improve organizational access to analytics by lowering technical barriers to data exploration. As natural language processing technologies become more advanced, conversational analytics systems are expected to support increasingly complex analytical queries and provide richer contextual explanations for data-driven insights (Gartner, 2021).

12.2.1 Query-Based Analytics

Query-based analytics systems enable users to retrieve analytical results through natural language queries. These systems translate human language questions into structured analytical operations, allowing users to access relevant insights without interacting directly with complex analytical tools (Sharda et al., 2020).

12.2.2 Conversational BI Systems

Conversational business intelligence systems integrate natural language processing with traditional BI platforms. These systems allow users to engage in dialogue-like interactions with data platforms, enabling iterative exploration of datasets and facilitating a more dynamic analytical process (Gartner, 2021).

12.2.3 Natural Language Interfaces for Data

Natural language interfaces enable organizations to democratize access to data analytics. By allowing employees across different departments to interact with analytical systems through natural language, these interfaces support broader organizational participation in data-driven decision-making processes (Davenport & Bean, 2018).

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12.3 Decision Intelligence Systems

Another emerging direction is the development of decision intelligence systems, which integrate analytics technologies with decision-support frameworks. Decision intelligence extends traditional analytics by focusing not only on data analysis but also on the processes through which analytical insights influence organizational decisions (Sharda et al., 2020).

These systems combine data analytics, artificial intelligence, and decision theory to improve the quality and consistency of decision-making processes. By integrating analytical outputs directly into decision workflows, organizations can reduce uncertainty and improve the reliability of strategic and operational decisions (Davenport & Bean, 2018).

12.3.1 Integration of Analytics and Decision Systems

The integration of analytics with decision systems allows organizations to move beyond descriptive and predictive analytics toward more actionable insights. Analytical models can be embedded within operational systems, enabling real-time decision support based on continuously updated data (Sharda et al., 2020).

12.3.2 AI-Augmented Decision Support

AI-augmented decision support systems combine machine learning algorithms with human expertise. These systems provide recommendations based on analytical models while allowing decision-makers to incorporate contextual knowledge and organizational experience into the final decision process (Davenport & Bean, 2018).

12.3.3 Decision Automation

In certain operational contexts, decision intelligence systems can enable automated decision-making processes. Automated decisions are particularly useful in environments where rapid responses are required, such as fraud detection, supply chain management, or dynamic pricing systems (Sharda et al., 2020).

12.4 Integration with Large Language Models

Recent advances in large language models (LLMs) are creating new opportunities for the integration of natural language technologies with analytical platforms. LLMs can serve as analytical interfaces capable of interpreting datasets, generating explanations for analytical results, and assisting users in exploring complex information environments (Davenport & Bean, 2018).

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These models can also support the generation of narrative explanations for analytical outputs, helping users understand the implications of data patterns and analytical predictions. As a result, LLMs have the potential to significantly enhance the communicative dimension of analytics by enabling more interactive and adaptive forms of data storytelling (Gartner, 2021).

12.4.1 AI Copilots for Analytics

AI copilots are intelligent assistants integrated into analytical platforms. These systems guide users through analytical workflows, suggesting relevant queries, highlighting important patterns, and generating explanatory narratives based on the underlying data (Gartner, 2021).

12.4.2 Automated Data Narratives

Automated narrative systems can generate contextual explanations for analytical outputs by combining statistical insights with natural language descriptions. These narratives help organizations communicate analytical findings more effectively across different organizational levels (Davenport & Bean, 2018).

12.4.3 Human-AI Collaboration in Data Interpretation

The future of data storytelling is likely to involve closer collaboration between human analysts and AI systems. While AI can automate certain analytical processes, human expertise remains essential for interpreting insights within broader organizational contexts and ensuring responsible use of data-driven narratives (Sharda et al., 2020).

13. Conclusion

The growing complexity of organizational data environments has increased the importance of effective methods for communicating analytical insights. While traditional business intelligence systems focus primarily on data processing and visualization, recent research emphasizes the need to integrate narrative structures into analytical communication. Data storytelling has emerged as an important framework that combines data visualization, contextual interpretation, and narrative techniques to facilitate understanding and support decision-making processes. By bridging the gap between data analysis and human cognition, storytelling with data enables organizations to transform complex analytical outputs into actionable insights (Knaflic, 2015; Few, 2013).

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This study examined the theoretical foundations, structural components, and organizational applications of data storytelling in the context of business intelligence and analytics. The discussion highlighted how narrative-oriented approaches can enhance the interpretability of dashboards, improve communication between analysts and decision-makers, and support more effective data-driven decision-making practices (Sharda, Delen, & Turban, 2020).

The analysis presented in this article highlights several key findings regarding the role of storytelling in data analytics. First, effective analytical communication requires more than accurate data visualizations; it also requires contextual explanations that guide users toward meaningful interpretations of data patterns. Narrative structures are theoretically positioned to help transform isolated metrics into coherent analytical explanations that may surface relationships, trends, and strategic implications — a claim that is plausible and partially supported by controlled experimental evidence (Shao et al., 2024; Pozdniakov et al., 2023), but that should be understood as conditionally rather than universally effective, and that requires empirical validation in naturalistic organizational settings before strong causal conclusions can be drawn.

Second, the integration of storytelling techniques into business intelligence environments can significantly improve the usability and interpretability of dashboards. When visualizations are combined with narrative annotations and structured explanations, users may be better positioned to understand the significance of analytical results — an effect with experimental support for single-insight comprehension tasks (Shao et al., 2024), qualified by evidence that multi-insight integration tasks do not show consistent benefit from narrative structuring, and that audiences' visualization literacy moderates the direction and magnitude of these effects (Franconeri et al., 2021; Pozdniakov et al., 2023).

Third, the organizational applications discussed in this study demonstrate that storytelling with data can support decision-making across multiple domains, including strategic management, marketing analytics, financial analysis, and operational performance monitoring. In these contexts, narrative dashboards help reduce the communication gap between technical analysts and managerial decision-makers (Davenport & Harris, 2007).

From a theoretical perspective, this study contributes to the literature by synthesizing concepts from data visualization, business intelligence, and narrative communication into an integrated framework for analytical storytelling. While prior research has examined visualization techniques and analytics-driven decision-making separately, this study emphasizes the importance of narrative structure as a critical component of effective analytical communication (Hullman & Diakopoulos, 2011).

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By conceptualizing data storytelling as a multidimensional process that integrates visualization, interpretation, and narrative context, this research extends existing models of business intelligence communication. The proposed framework highlights how narrative elements can enhance the interpretability of analytical outputs and support more meaningful engagement with data-driven insights (Sharda et al., 2020).

Additionally, the study contributes to the growing field of narrative visualization by emphasizing the role of storytelling in organizational decision-making environments. This perspective expands the analytical focus beyond technical data processing to include the communicative and cognitive dimensions of analytics (Hullman & Diakopoulos, 2011).

The findings of this study also have important practical implications for organizations seeking to improve the effectiveness of their analytical communication practices. One key implication concerns the design of business intelligence dashboards. Rather than presenting large collections of isolated metrics, dashboards should incorporate narrative structures that guide users through the analytical story represented by the data (Few, 2013).

Another implication involves the role of analysts and data professionals in communicating insights. Analysts increasingly need skills that extend beyond statistical analysis to include narrative communication and visualization design. The ability to construct clear and compelling analytical narratives can significantly improve how insights are understood and used within organizations (Knaflic, 2015).

Organizations should also consider investing in tools and processes that facilitate narrative-based analytical communication. Modern analytics platforms increasingly include features such as automated annotations, natural language explanations, and interactive storytelling capabilities that support more effective data interpretation (Sharda et al., 2020).

Despite its contributions, this study presents limitations that are fully documented in Section 2.4 under three categories — methodological, conceptual, and empirical — and are summarized here in terms of their implications for the interpretation of the article's conclusions. Methodologically, the absence of empirical validation for the five-layer framework and the structural survivorship bias of the evidence base mean that the framework's design principles should be treated as theoretically grounded heuristics rather than empirically verified specifications. Conceptually, the disciplinary scope of the theoretical frameworks employed — concentrated in North American and Northern European cognitive science and organizational behavior traditions — limits the direct applicability of the conclusions to organizational contexts that differ substantially in cultural norms, decision-making structures, and relationships between

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data and authority. Empirically, the evidence base on data storytelling effectiveness remains concentrated in laboratory settings and specific sectors, and the generalizability of experimental findings to the full range of organizational decision environments examined in this article has not been established. These three categories of limitation are interconnected: the methodological constraint of absent empirical validation means that the conceptual and empirical limitations cannot yet be resolved through the framework itself, and their resolution constitutes the most consequential agenda for future research in this domain. Future research will therefore be necessary to evaluate how emerging technologies influence the effectiveness of narrative-based analytical communication (Davenport & Bean, 2018).

Future research should explore several directions that could further advance the understanding of storytelling in analytics environments. One promising area involves empirical studies that evaluate the effectiveness of narrative dashboards compared to traditional visualization approaches. Experimental research could examine how narrative structures influence decision accuracy, user engagement, and cognitive comprehension of analytical information.

Another important direction involves the integration of artificial intelligence technologies with storytelling frameworks. As AI-driven analytics platforms continue to evolve, automated narrative generation and natural language interfaces may play an increasingly significant role in analytical communication (Davenport & Bean, 2018).

Additionally, future studies should investigate the role of human–AI collaboration in data interpretation. While AI systems can assist in identifying patterns and generating narrative explanations, human analysts remain essential for contextualizing insights and ensuring responsible interpretation of data-driven narratives.

By continuing to explore these emerging research directions, scholars and practitioners can further refine the role of storytelling in analytics and contribute to the development of more effective data-driven decision-making systems.

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