UNPACKING DATA STRATEGIES – CONCEPTUALIZATION AND EMPIRICAL INSIGHTS

Completed Research Paper

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Abstract

Data is increasingly considered a strategic enterprise asset capable of driving competitive advantage. However, despite the increasing importance of data, the data strategy concept remains under-theorized, characterized by fragmented, heterogeneous perspectives and limited empirical insight into its formulation and implementation in organizations. Building on strategy literature from management and information systems, we derive a definition and conceptual framework for data strategy, which we use to examine data strategies in their organizational context. Drawing on multiple case studies, we provide nuanced insights into the development of data strategy, its key constituents, its impact, and its interdependencies with the organizational strategy landscape. Our findings highlight data strategy as an organization-wide and self-contained strategy and shed light on its configuration. In addition, we contribute to practice by outlining the key elements and current status of data strategy in organizational settings.

Keywords: Data Strategy, Data Studies, Data Value, Artificial Intelligence, Case Study.

1 Introduction

Data has traditionally been treated as a by-product of economic activity (Wang et al., 1998). However, its role has evolved into that of a strategic asset with an organization-wide scope, enabling firms to generate and sustain competitive advantage (Grover et al., 2018; Xu et al., 2024). Empirical studies suggest that data-driven organizations outperform others in terms of both productivity and profitability (Côrte-Real et al., 2017; McAfee & Brynjolfsson, 2012; Quaadgras et al., 2014). Recent advances in (generative) artificial intelligence (AI), which support a wide range of applications, from enhancing decision-making to content creation and enabling knowledge work, further amplify the strategic relevance of data (Berente et al., 2021; Feuerriegel et al., 2024). Consistent with these findings, executives increasingly recognize that data, analytics, and AI are central in the transformation of their business (Bean, 2026), which in turn requires building data-related capabilities (Grover et al., 2018).

However, despite substantial investments and repeated declarations of data as a critical organizational asset, most organizations still encounter significant challenges that hinder the organizational scaling of data and AI initiatives or lead to their failure (Browder et al., 2022; Haefner et al., 2023; McKinsey, 2025). Among these challenges are persistent issues related to data quality, the modernization of data and analytics infrastructures for data storage, processing, provision, and use alongside measures to ensure security and protection against cybercrime (Baesens et al., 2016; Bayrak, 2021). At the same time, many challenges are rooted in organizational factors, including unclear responsibilities, insufficient skills, or concern the need for cultural or mindset shifts (Baijens et al., 2020). With AI, new risks emerge, such as inaccurate, biased, or unethically sourced data, which can negatively affect business operations and public perception (Breidbach & Maglio, 2020). Ultimately, these challenges constrain the organization's ability to extract value from data (Baecker et al., 2020; Nagle & Sammon, 2017).

Addressing these challenges requires adopting a more strategic approach towards data and making informed decisions about the use of organizational data resources and technology such as AI (Berente et al., 2021). To realize value from data, companies must take deliberate decisions related to resource allocation and orchestration (Trieu, 2017; Xu et al., 2024), aligning priorities and investments for data with the organization's strategic purpose (Aral & Weill, 2007). While both academic and practitioner literature have occasionally called for more strategic planning and management of data (Goodhue et al., 1992) or emphasized the need for explicit data strategies (DalleMule & Davenport, 2017), the data strategy construct remains under-theorized. In addition, there is limited empirical insight into how data strategies are formulated and implemented in organizations, constraining a comprehensive understanding of their role in practice. To address these gaps and overcome the fragmented state of knowledge, this study investigates the following research question: *How should data strategy be conceptualized, and how is it developed and implemented in organizations?*

To address this question, we adapt Chen et al.'s (2010) conceptualization of information systems (IS) strategies into the context of data strategy and use it as an analytical framework to examine data strategies in their organizational context. Our research perspective (Clarke & Davison, 2020) reflects the viewpoint of executives with organization-wide data and AI responsibilities (Lee et al., 2014) who are involved in the formulation and implementation of data strategies. By employing multiple case studies (Yin, 2018), we gained a nuanced and in-depth understanding of data strategies embedded within a broader organizational context across 13 European companies that vary in terms of their industry, strategic contexts, data scope, and use cases. Using the key concepts based on our analytical framework, we derived empirical insights on (1) the data strategy development process, (2) data strategy constituents, (3) data strategy impact, and (4) alignment within the organizational strategy landscape. Our study makes two main contributions to IS literature and the emerging field of data studies (Aaltonen et al., 2021; Benfeldt & Persson, 2025): First, we unpack data strategies as distinct organizational constructs and advance their conceptualization, building on foundational concepts from management and IS strategy literature. Second, we provide empirical insights into their development and implementation in organizations.

The remainder of the paper is structured as follows: In the next chapter, we review relevant strategy literature and develop a conceptualization of data strategy. We then present the applied case study methodology. Subsequently, we present our case insights based on the analytical framework. Finally, we conclude by discussing the theoretical and practical contributions of our study.

2 Background

2.1 The Strategy Concept in Management and IS Literature

Originally rooted in military doctrine, the concept of strategy has been widely studied in management research (Chen et al., 2010). Strategic decisions are typically distinguished from operational or tactical decisions (Ackoff, 1970; Johnson et al., 2005) by their long-term orientation, their irreversibility, and their profound implications for firm performance. A substantial body of literature has sought to define strategy (Fahey & Christensen, 1986; Mintzberg, 1987; Porter, 1996) and to provide managers with frameworks that guide the understanding of competitive dynamics, identification of value creation opportunities, and strategic decision-making (Chen et al., 2010). To structure these different conceptualizations, Mintzberg (1987) proposed the five "Ps of strategy", which articulate five competing but interrelated definitions and have since shaped the strategy discourse in both the strategic management domain and IS literature. In this framework, strategy may be understood as a plan, that is, a deliberate course of action designed by corporate management; as a position, referring to the organization's place within its competitive environment; and as a pattern, reflected in the consistency of a set of actions. Furthermore, strategy can be viewed as a ploy, defined as a specific maneuver to create a competitive advantage; or a perspective, denoting the shared worldview or school of thought that influences an organization's strategic behavior. Mintzberg (1987) argues that each definition has its own legitimacy and purpose, together providing a holistic understanding of strategic behavior. To trace the evolution of the strategy concept in academic research, Ronda-Pupo and Guerras-Martin (2011) conducted a comprehensive co-word analysis of key terms in scholarly publications from 1962 to 2008. Based on this longitudinal examination, they distilled the core of the strategy concept as *"[...] the dynamics of the firm's relation with its environment for which the necessary actions are taken to achieve its goals and/or to increase performance by means of the rational use of resources"* (Ronda-Pupo & Guerras-Martin, 2011, p. 183).

From the broader management literature, many subdomains of the strategic discourse have emerged, including IS strategy and digital strategy, which address the growing strategic significance of digital and information technologies (IT) within organizations. IS strategy research has traditionally focused on the management of digital information technologies, conceptualized as a combination of information, computing, communication, and connectivity technologies (Bharadwaj et al., 2013). In its early conception, IT strategy – often used interchangeably with IS strategy – was understood as a functional-level strategy subordinate to business strategy, primarily aimed at supporting and enabling business objectives (Bharadwaj et al., 2013). In contrast, Chen et al. (2010, pp. 236–237) build on Mintzberg's (1987) fifth "P" to define IS strategy "as a shared organizational perspective on setting and meeting organizational goals the investment in, deployment, use, and management of information systems", indicating that IS strategy should be examined at the organizational level rather than the functional level. Due to its organization-wide scope, IS strategy should be seen as part of corporate strategy rather than business strategy, although being aligned with the latter (Earl, 1989).

As the significance of digital technologies for organizations has increased, the need to align IT and business within IS strategy has intensified, leading to the progressive dissolution of boundaries between the two domains (Gür et al., 2021). This convergence between IS and business strategy has ultimately resulted in the emergence of another stream of research that considers digital (business) strategy as equally business-centric and technology-inspired (Bharadwaj et al., 2013; Chanias et al., 2019). Accordingly, a digital strategy focuses on leveraging digital resources to create differential value for organizations (Bharadwaj et al., 2013). However, digital strategy does not replace other strategies, but needs to coordinate and align with existing sub-strategies (Chanias et al., 2019).

2.2 Research on Data Strategy

Although the term data strategy is frequently referenced by practitioners (e.g., DalleMule & Davenport, 2017; Ransbotham et al., 2024), research offers fragmented and heterogeneous perspectives on the concept. A generalized understanding of data strategy and a widely accepted definition remain elusive (Grossman, 2018). It is important to note that as early as in the 1990s, Goodhue et al. (1992) proposed strategic data planning to address the insufficient logical integration of data in information processing systems and to meet business needs. Focusing on the definition of shared data across different organizational functions and on data architecture as a guide for future systems development, they proposed five categories of potential outcomes of strategic data planning: the implementation of integrated systems, the development of a data architecture, the identification of systems priorities, the rethinking of business processes, and education and communication. Subsequent research has suggested strategies for data quality management or the conceptualization of data quality in organizations (Falge et al., 2013; Otto, 2015), thereby emphasizing the fitness of data for intended purposes.

With the increasing relevance and criticality of (big) data for organizations, discussions on data strategies increasingly incorporated organizational facets and business objectives. For instance, Davenport (2014) examined desirable objectives for utilizing big data, differentiating between cost reductions, reducing process times, developing new product and service offerings, or supporting internal business decisions. DalleMule and Davenport (2017) highlight the critical need for a data strategy that is not only defensive, minimizing downside risks associated with accomplishing organizational objectives such as ensuring regulatory compliance, mitigating fraud, and ensuring data integrity. Instead, a data strategy should also address the offensive objectives of creating value from data by supporting business targets such as increasing revenue and customer satisfaction or supporting managerial decision-making. With a similar perspective, Grover et al. (2018) outline how organizations create strategic business value from big data analytics, distinguishing between functional values such as efficiency gains or market share and symbolic values such as reputation gains and reduced environmental pressure. Spanning both dimensions, they identify four strategic roles that organizations can pursue: reactive defender, image builder, performance enhancer, and strategic transformer. While DalleMule and Davenport (2017) addressed the interaction between data offense and data defense as investment trade-offs and the design of organizational data and information architecture, existing academic works still offer limited recommendations for the design of data strategies for organizations.

Given the considerable variation in approaches to data strategies, Gür et al. (2021) develop a taxonomy that systematizes data strategy tools and methodologies from academic and practitioner literature. They categorize them along several dimensions, including the objective of data strategy and its scope, strategic statement, business-IT alignment, and strategy implementation. More recently, Baecker et al. (2025, p. 1), building on Piccoli et al. (2022), define data strategy as “a synthesis of an organization's strategic data initiatives – competitive moves that depend on digital data resources to create and appropriate economic value.” They develop a data strategy taxonomy to manifest the key characteristics of data-based strategy-making, including organizational data, its orchestration, and business value, and conduct a cluster analysis to derive four strategy types of data-based value creation (Baecker et al., 2025). To compare these fragmented conceptualizations of data strategy in the literature, we summarize prevailing understandings in Table 1 and classify them according to Mintzberg’s (1987) perspectives of strategy.

Reference	**Understanding of strategy**	**Strategy discourse according to Mintzberg (1987)**
Goodhue et al. (1992)	“Strategic data planning” that builds a data-centered model of the organization by defining a data architecture to guide information system developments that meet business needs	Strategy as a formalized, top-down, data-centered plan
DalleMule and Davenport (2017)	Data strategy as an organization-wide framework that balances defensive control and offensive value creation, enabled by a defined data architecture	Strategy as a conscious position choice along the spectrum between defense and offense
Grover et al. (2018)	Data strategy framed as building big data analytics assets and capabilities as valuable resources to generate functional and/or strategic business value	Strategy as a perspective on valuable data resources with a business orientation focused on value creation
Baecker et al. (2025)	Data strategy as a synthesis of an organization's strategic data initiatives, linking data, its orchestration and business value creation	Strategy taxonomy as a plan for allocating data resources to create value, and strategic types reflecting strategy as a position

Table 1. Data strategy conceptions in the literature.

2.3 Towards a Unified Understanding of Data Strategy

Despite the critical importance of data strategy and its adoption in practice, we still lack a holistic and coherent academic understanding of data strategy that builds on foundational concepts from management and IS strategy literature. To address this gap, we draw on Ronda-Pupo and Guerras-Martin’s (2011) synthesis of the strategy concept and Mintzberg’s (1987) strategy as a plan, and define data strategy as “*a comprehensive, organization-wide plan that specifies how data and complementary resources are allocated, governed, and utilized to achieve organizational objectives and/or increase performance*”. According to this definition, data strategy encompasses not only data provision and governance, but also the organizational use of data, thereby serving as the conceptual foundation for analytics or AI (sub)strategies. The definition also highlights complementary resources that comprise intangible and human resources, as well as further technological resources, e.g., to analyze data in order to achieve the specified objectives (Gupta & George, 2016).

To further contribute to the theorization of data strategy, we adapt the seminal work on IS strategies by Chen et al. (2010) to the context of data strategy. Accordingly, we conceptualize data strategy through four distinct but interrelated contextual elements, which are depicted in Figure 1: (1) A *strategic development process* with defined ownership and responsibilities, as well as initiating drivers. (2) The *data strategy* reflects the output of this process, consisting of underlying key elements such as strategic initiatives and required capabilities. (3) The *purposeful implementation of the strategy* results in *desired impacts*. Importantly, data strategies do not operate in isolation within organizations but rather are interdependent with the (4) *organizational strategy landscape*, which shapes their development, constituent elements, and impacts, requiring alignment. Through this conceptualization, we retain Chen et al.'s (2010) key rationale of the strategy's organization-wide orientation, its organizational embedding through processes and impacts, and its strategic interdependencies.

This conceptualization provides a theoretical foundation for data strategy and serves as an analytical framework to guide the empirical analysis of data strategies in organizations using a multiple case study approach, which is described in the following section.

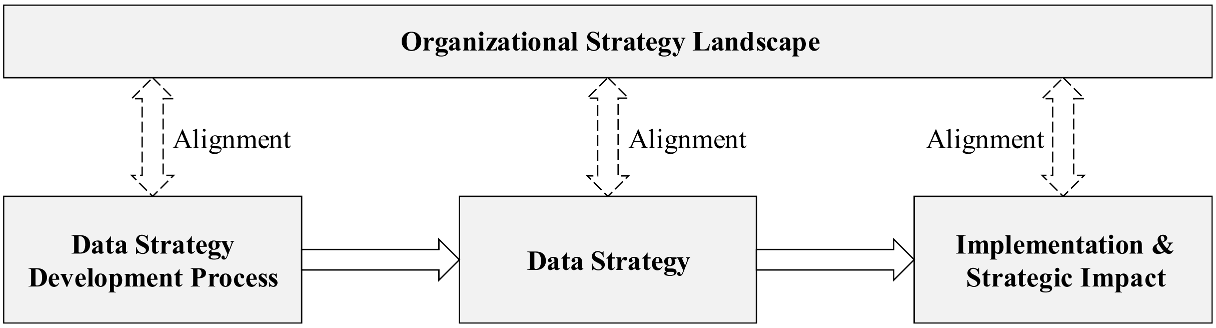

Figure 1. Conceptual framework for data strategy, adapted from Chen et al. (2010).

3 Methodology

To study the current state of data strategies in organizations, we employed case study research, which is suitable for gaining insights into investigated phenomena in natural settings and for developing theory from existing knowledge in practice (Benbasat et al., 1987). In particular, the inclusion of multiple cases ensures the validity of the results and analytical generalizability (Yin, 2018). Ultimately, the findings from multiple cases enable the identification of patterns upon which rigorous theories can be built (Ketokivi & Choi, 2014).

3.1 Case Selection

Through two ongoing industry-research programs, we have trusted relationships with a large number of European-based firms across various industries with whom we are working on topics related to the management and value creation from data. Following purposeful sampling (Yin, 2018), we selected 18 European organizations with an advanced level of maturity in the adoption of data and AI to participate in a study on data strategy. The selected organizations varied in terms of their industry as well as the objective and scope of their data strategies, which allowed us to identify commonalities and divergences among the participating organizations. We were interested in gaining an in-depth understanding of their data strategy as defined and governed at an organization-wide level, which represents the unit of analysis of this study.

3.2 Data Collection

To gain profound insights into the organization's context and data strategy, we collected primary data through in-depth expert interviews. For each case, we selected key informants who held relevant roles with decision-making authority and oversight responsibilities over the organization's data strategies, such as Head Data Analytics & AI, Head of Data Office, or Chief Data Officer, to reflect the study's managerial perspective. In addition, interviewees had to have a minimum affiliation with the organization (> 2 years) as well as knowledge of the history of their data strategy and data and AI initiatives to ensure familiarity with the organization's data strategy.

Three researchers conducted semi-structured interviews with the participants via video conference. Prior to commencement of the interviews, we informed the interviewees about the purpose of the study, the confidentiality of the data, and the interview structure. The interviews, lasting between 50 and 90 minutes, were recorded and transcribed for analysis using established digital tools to enable the documentation of the original richness of the data for further analysis. We used an interview guideline that covered eight parts to holistically cover the data strategy, its development process, impact, and alignment with other strategies in the organization.

In addition to the interview data, we gained access to and reviewed internal company documents, including company presentations and data strategy documentation. We completed the data collection by searching for relevant public sources on the data strategies of the case organizations, such as keynotes, press articles, and their website. These different data sources facilitated the triangulation of the information documented during the interview. By verifying the claims from the expert interviews with the organizations' documented practices, e.g., on governance structures and data initiatives, the validity of the findings was ensured (Yin, 2018). Finally, we returned our case documentation to the interview participants for review to confirm our understanding and clarify remaining questions.

During the interviews, we found that 5 out of the 18 organizations lacked a documented and communicated data strategy. Instead, they relied on implicit strategic assumptions, although they were advanced in their data and AI initiatives. Thus, we narrowed the sample to 13 organizations suitable for analysis in order to gain profound insights into their data strategy. A summary of the participating organizations and the characteristics of their data strategy's contextual elements is provided in Table 2.

ID	Industry & case	Interviewee's role	Data strategy development	Data strategy	Implementation and impact	Organizational strategy interdependencies
1	Financial Services	Head of Data Office	Mix of top-down steering and use case-driven bottom-up development	Organization-wide data strategy with focus on defense, business unit offense, with current shift towards data foundation	Business value focus with defined success matrix and periodic steering, resulting in first measurable efficiency gains	Data use cases are tied to business goals, connections to risk & compliance strategy
2	Financial Services	Chief Data Officer	Bottom-up grounded and top-down triggered development process	Organization-wide data strategy, enabling AI as a prerequisite	Implementation cascading down from management, set impact metrics with value focus on cost efficiency and downside risks	Data Strategy emerges from business strategy and is linked to IT and risk strategies, alignment to AI strategy
3	Financial Services	Head Data Analytics & AI	Bottom-up development based on organizational as-is analysis	Group-wide defense strategy, divisional offense strategies covering AI; standalone organization-wide generative AI strategy	Domain-specific implementation with cross-functional collaboration, value focus on ensuring defense and realizing efficiency gains	Data strategy derived from business strategy, connections to generative AI strategy, involvement of risk and compliance
4	Financial Services	Head of Bank Organization and IT	Designed by analytics department and reviewed by senior management	Group-wide functional data strategy covering offensive and defensive aspects	Business first implementation embedded in business portfolio management, first quality and governance benefits	Data strategy is linked to business strategy and aligned with IT and risk strategies
5	Financial Services	AI & Data Strategy Lead & Deputy Head of Data & AI	Waterfall-like development, mandated by organization-wide committee	Organization-wide data & AI strategy covering offensive and defensive aspects	Implementation anchored in corporate processes with focus on scaling use cases, detailed value measures from use cases to data literacy	Data strategy is linked to business strategy and aligned with risk and information security
6	Chemicals	Head of Data Excellence, Manager Group Data Office	Combination of top-down by central data office and bottom-up incorporating expert inputs	Group-wide data strategy focussing on foundational support	Federated data strategy roll-out in divisions, coordinated by digital councils, focus on enabling AI use cases, defined objectives and key results	Data strategy is strongly aligned with the digital roadmap and AI strategy
7	Manufacturing	Head of Global Data Governance	Jointly developed by Center of Data Excellence and data domains	Group-wide defensive data strategy focussing on providing high quality master data in high-priority data domains	Focus on implementing a central master data management system and policies, established master data hub as first result	Data strategy is aligned with business (divisional) strategies, IT strategy and digital products/services strategy

8	Pharma	Global Head of Data & AI Governance, Global Head of Group Data Strategy	Systematic top-down strategy process, inspired by practitioner literature	Group-wide data strategy with emphasis on people, aiming at provision of insights from data, covering the use of AI	Communication and change management as priority, incorporated progress metrics, e.g., case adoption, upskilling, training attendance	Strong links to business strategies (segments/functions)
9	Oil & Gas	Group Chief Data Officer	Development by the team in the Group Chief Data Office	Group-wide data strategy centered around clear, accessible, reliable data to extract value (CARE)	Roll-out through domain data strategies, monitoring with maturity assessment, difficulties in demonstrating impact	Rather weak links to other strategies
10	Insurance	Group Data Management Lead, Group data & AI transformation lead	Systematic top-down strategy process	Group-wide data and AI strategy, aiming at transformation, GenAI and innovation	Group initiatives, and local data strategies, key performance indicators to measure success, including maturity, time to market, value generated, culture	Strong business-driven approach, data and AI are enabling the business strategy
11	Packaging	Director Data Management, AI and Analytics	Iterative development starting with business inputs (challenges and visions) and balanced with security, legal, architecture, processes	Group-wide data strategy, focussing on why, who and how and enabling the strategic pillars of business strategy	Implementation boosted by integration to business strategy, defined quarterly progress reports	Strong integration with business strategy, input to other existing strategies (e.g., security, IT)
12	Medtech	Director Data Intelligence & Data Innovation	Maturity assessment as starting point, development driven by data management and analytics teams	Organization-wide data strategy focussing on data-centric organization	Few adopted metrics such as number of use cases and adoption	Data and analytics/AI enabling digital excellence and thereby the future business strategy
13	Manufacturing	VP Strategic Data Management	Systematic process driven by strategic data management team and approved by data council	Group-wide data strategy to manage "data as a differentiating asset", derived from business strategy	Roll-out in domain-specific data strategies, currently no monitoring of domains but maturity assessments for data management and analytics	Digitalization strategy connects business, IT and data, further link to AI strategy

Table 2. Participating organizations and characteristics of their data strategy's contextual elements.

3.3 Within and Cross-Case Analysis

To advance theorization on data strategy, we applied abductive reasoning as it allows for embedding empirical findings into an existing theoretical model through the iterative combination of induction and deduction (Van Maanen et al., 2007). Our theorization process was initiated by observations of data strategies that have evolved within the organizations in our industry-research collaborations, which could not be fully explained by existing theories. Moreover, data strategies often coalesce around strategic initiatives (Baecker et al., 2025), thus being closer to implementation than corporate strategies and reflecting aspects of their development and implementation more extensively. To investigate the phenomenon of interest, we engaged in an iterative process of explanation seeking based on data collection and existing theories.

Two researchers coded the collected case data. Our coding process started with labeling the interview transcripts and supporting documents with first-order codes. We then searched for relationships and patterns in the first-order codes, aggregating them into second-order codes. During this process, we continuously engaged with existing strategy literature to make sense of the observations. The conceptual framework of data strategy (cf. Figure 1) was then applied to systematize the findings. Accordingly, we applied the contextual elements of the development process, strategy, impact, and strategy interdependencies as deductive code categories. We then assigned the inductively identified second-order codes to the deductive codes created. This process allowed us to identify inductive categories from the empirical findings that were not sufficiently explained in the previous conception of data strategy, enabling us to expand the existing theoretical framework (Van Maanen et al., 2007). The figure below depicts our coding and theorizing process, illustrated by examples of our data analysis.

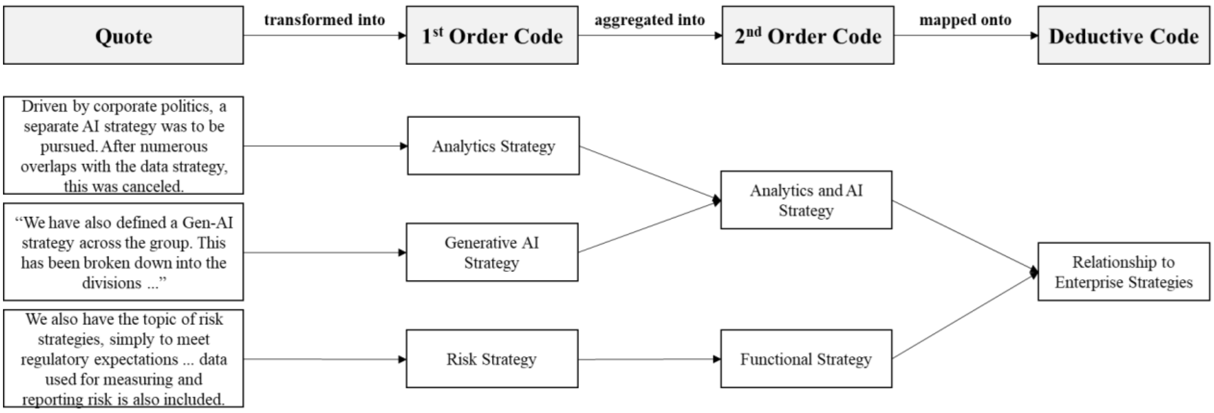

Figure 2. Data analysis process.

After coding the cases separately, we conducted a cross-case analysis, which supports the aggregation, simplification, and generalization (Miles et al., 2013). Within a comparative analysis of all 13 cases, we iteratively searched for differences and similarities between the organizations. Thereby, we reviewed the created second-order codes, which we use to explain the deductive conceptual framework of data strategy and thus for holistic reflection of the data strategies, including their development process, strategy constituents, impacts, and implementation, as well as interdependencies within the organizational strategy landscape. Ultimately, this process enabled not only the identification of data strategy configurations across organizations, but also their status, revealing differences and similarities in development and perception. The case insights are described in the following chapter.

4 Empirical Insights on Organizational Data Strategies

The insights gained from the 13 case studies provide a nuanced understanding of how data strategies are configured in practice. They show that data strategy has become an established and increasingly institutionalized managerial practice with significance at the executive level. The current momentum around organizational AI adoption accelerates efforts to define, adapt, or extend data strategies across organizations. However, our empirical insights indicate that data strategies did not solely emerge in response to AI. In several mature organizations, particularly in industrial sectors (e.g., cases 6, 8, and 13), current data strategies iteratively evolved from master data or business intelligence strategies. In other organizations, ongoing data- and AI-related initiatives triggered the development of an explicit data strategy, although some of these efforts did not qualify as sufficiently well-defined data strategies and were therefore excluded from the analysis. Among the more mature organizations, data strategies are typically defined organization-wide or at the group level, and in some cases (e.g., cases 6 and 10) further differentiated for individual divisions or business units in line with the organizational structure. Table 3 summarizes the cross-case findings across the four contextual elements of data strategy, which are discussed in detail in the following subsections.

Contextual element	**Cross-case patterns, including significant variations**
Data strategy development process	• Triggered by a constellation of regulatory, strategic, and technological motivations • Guided emergence, combining top-down direction with bottom-up learning • Responsibility with a central data office or hub operating under executive sponsorship and supported by cross-functional committees • Variations in organizational anchoring between centralized roles and federated domain/division ownership (e.g., cases 5 vs. 6)
Data strategy constituents	• Vision for data as a strategic resource articulated in relation to overarching business objectives • Ambidextrous design that balances value creation with control and risk mitigation • Key elements include portfolios of data initiatives and use cases, as well as governance, data/technology architecture, and cultural measures to establish foundational capabilities • Varying strategic focus from master data/governance to organizational transformation and innovation (e.g., cases 7 vs. 10)
Data strategy implementation and strategic impact	• From executive communication, implementation cascades throughout the organization with cross-functional collaboration • Initial impacts are primarily enabling and defensive, such as established governance and higher data quality • Monitoring is mainly based on progress and maturity indicators, outcome metrics only in a few cases (e.g., in cases 1 and 10) • Varying scope of measurement, ranging from extensive value metrics to limited monitoring (e.g., case 1 vs. 13)
Alignment with organizational strategy landscape	• Strong link between data and business strategies • Further interdependencies with IT/IS strategies and digital roadmaps, and in regulated industries with risk, compliance, and security strategies • AI is typically integrated into data strategy; for separate AI or GenAI strategies, explicit interdependencies with data strategy exist (e.g., cases 8 vs. 2) • Mutual interdependence, such as data strategy enabling business objectives (e.g., case 12), but being constrained by regulatory and risk requirements (e.g., case 5)

Table 3. Cross-case synthesis across the four contextual elements of data strategy.

4.1 Data Strategy Development Process

Across the cases, the development of data strategies is triggered by a constellation of regulatory, strategic, and technological motivations. In several instances, particularly in the financial services sector, regulatory requirements and anticipated expectations (e.g., related to data quality and security) act as key triggers for the formalization of data strategies. Compliance considerations also play an important role in other industries, particularly in relation to sustainability and traceability. Beyond regulatory drivers, organizations are increasingly motivated by strategic ambitions to enhance business performance and to enable digital or data-driven business models. For example, surveyed organizations (e.g., case 10) aim to increase operational efficiency, accelerate data access, improve data quality, and create actionable insights for managerial decision-making. Additional industry-specific stimuli arise from efforts to augment physical products with digital capabilities. Direct data monetization, however, plays a minor role in driving data strategy development. Ultimately, technological dynamics, notably the market diffusion of generative AI, heighten the perceived urgency and visibility of data as a strategic asset. Periodic, board-mandated reviews and organizational realignments further catalyze strategy adjustments and revisions.

The development of data strategies across cases follows multiple entry points but converges toward a hybrid approach that combines top-down direction with bottom-up learning. In some organizations, data strategy development is initiated top-down, embedded within organizational strategy cycles, or driven by explicit management directives. In others, it emerges bottom-up from data and AI use case pipelines that eventually require superordinate steering, or from evidence-based assessments of current data maturity (e.g., case 13). Across most cases, organizations adopt a hybrid approach grounded in identified fundamental challenges or opportunities and corresponding management directives. Evaluation and decision mechanisms are typically implemented sequentially and supported by continuous steering and portfolio management in the organizations. Within this process, key strategy components, such as use cases and the required capabilities, are systematically prioritized and funded. This hybrid approach closely aligns with Mintzberg's (1987) notion of guided emergence, whereby strategy is intentionally directed by leadership while simultaneously evolving through learning and action across the organization.

Defined ownership anchors both the data strategy and its development within the organization. Responsibilities are typically centralized in a data office or data hub operating under explicit executive sponsorship. Depending on organizational size and structure, this central office is complemented by federated structures and designated roles at the level of divisions, business units or functions. To ensure organization-wide alignment, the data office is usually supported by cross-organizational committees, involving key business stakeholders as well as representatives from governance, risk, security, and architecture. These committees support the coordination and integration of the data strategy across affected organizational areas.

4.2 Data Strategy Constituents

Beyond strategy formation, the cases also shed light on the substantive content of data strategies. At their core, data strategies typically begin with a vision that articulates the role of data in relation to overarching business objectives, emphasizing value creation from data and performance improvement. In several organizations, data – often in conjunction with AI – is positioned as a critical enabler of strategic business opportunities (e.g., case 10). In some instances, this positioning extends to shaping the business strategy itself, particularly when data becomes a differentiating strategic asset that is reliable, accessible, and purposefully used.

To operationalize the vision, data strategies document focus areas and guidelines that direct organizational activities and investments. Typically, they specify data initiatives and use case portfolios, define roles and responsibilities, and ensure the compliant and ethical use of data regarding security, privacy, and fairness. Additionally, they outline architectures and technologies such as data platforms, data mesh approaches, or specific AI tools, and define cultural measures, including upskilling initiatives to improve data literacy. Across cases, data strategies exhibit an ambidextrous nature, combining defensive elements of control and risk mitigation with offensive objectives of value creation, both in their overarching vision and in their constituents. Beyond overall central steering, this dual rationale is structurally reflected in some cases in hub-and-spoke architectures (e.g., 1 and 3). Foundational defensive elements, such as specifications for data quality, platform architectures, and governance frameworks, are defined centrally at the group level, while offensive elements related to prioritizing and implementing value-creating use cases are distributed to business divisions. While the majority of the cases examined balance defensive and offensive elements, some organizations are shifting their priorities from data provision towards building foundational capabilities for subsequent value creation, partly in response to a prior focus on analytics and AI or to ensure regulatory compliance first. Nonetheless, many organizations advocate a pronounced “business-first” approach that integrates data strategy implementation into daily operations and corporate steering, rather than treating data strategy as an IT-centered artifact.

Finally, the cases highlight ongoing disagreement regarding the scope and boundaries between data and AI strategies. While the majority of organizations integrate AI as an offensive component of a superordinate data strategy, others establish dedicated AI or even generative AI strategies, which are, however, explicitly aligned with the data strategy.

4.3 Data Strategy Implementation and Strategic Impact

Developed data strategies are long-term oriented and periodically updated in defined cycles, typically ranging from one to three years, allowing organizations to adjust their strategic orientation to changing external or internal circumstances. At the same time, external factors may necessitate unscheduled revisions of data strategies.

Progress of the data strategy is typically monitored against a combination of progress and outcome metrics, as well as governance and maturity indicators. These include indicators capturing the development of organizational capabilities, such as the number of conducted trainings, or more comprehensive maturity assessments at the level of data domains. Outcome metrics are generally scarce, but may include the number of implemented use cases, time to market, and estimates of value generated, for instance, through cost savings or revenue contributions. The variety of applied metrics again reflects the ambidextrous character of data strategies, manifested in their development, constituents, and impacts. However, we observed a few cases that have yet to establish monitoring systems or remain hesitant due to difficulties in measurement.

Against this backdrop, the observed strategic impacts in the cases are heterogeneous and often nascent. Typically, tangible effects of data strategy implementation relate to defensive enablement, such as the establishment of roles and responsibilities, definition of architecture and standards, improvements in data quality, and the creation of preconditions for AI use cases. Additionally, some organizations report initial efficiency gains, such as time savings through process automation. Offensive results, such as the successful scaling of use cases and the expansion of the portfolio, in combination with revenue generation, remain sporadic. Overall, the findings suggest that data strategies initially tend to generate defensive impacts, while revenue-oriented effects require longer time horizons and higher levels of organizational maturity.

4.4 Alignment with Organizational Strategy Landscape

Finally, the cases reveal how data strategies are embedded and aligned with the organization's overarching strategic landscape. Similar to IS strategies (Chen et al., 2010), data strategies exhibit strong linkages to business strategies. In several organizations, the data strategy is derived directly from the business strategy, formalizing this connection by explicitly aligning strategic data priorities with business objectives, or even becoming an integral part of the business strategy (e.g., case 11). In cases where such direct integration is absent, data is nonetheless viewed as an enabler of future business opportunities and thereby linked indirectly to business objectives.

Beyond business strategy, the majority of organizations explicitly link data strategy to digital and technology-related strategies, such as digitalization roadmaps or IT agendas. For these endeavors, accessible, high-quality data provides a prerequisite, whereby the data strategy serves as an element of the infrastructure and governance foundation. In cases where separated data and AI strategies exist, a high degree of mutual dependence and alignment can be observed. While data strategies establish the foundation in terms of usable data assets, analytics and AI strategies specify how these assets are leveraged to create value. Finally, several organizations, particularly in the financial services sector, demonstrate strong alignment between data strategy and other business-critical functional strategies. Defensive elements of the data strategy, such as data quality and access rights, are typically linked to compliance, risk management, and security strategies. This reflects both regulatory requirements and the potential of data-related incidents to directly affect an organization's financial position or reputation. Overall, data strategies do not constitute isolated constructs but are deeply embedded in the strategic landscape of organizations, simultaneously positioning data as an enabler and a constraint in achieving overarching organizational objectives.

5 Discussion and Future Research

Despite the increasing importance of data, the data strategy construct remains under-theorized, with fragmented, heterogeneous perspectives and limited empirical insight into its formulation and implementation in organizations. To address these gaps, our study makes both theoretical and empirical contributions: First, we develop a definition of data strategy and propose a conceptual framework by adapting Chen et al.’s (2010) conceptualization of IS strategies to this context. Second, we provide nuanced in-depth empirical insights into how data strategies are defined, implemented, and embedded within a broader organizational context, based on multiple case studies with 13 European organizations. The findings emphasize that data strategies have become an institutionalized managerial practice that did not originate solely with the advent of AI, but have instead evolved over multiple iterations, often emerging from earlier master data or business intelligence strategies. The *data strategy development process* is mostly triggered by constellations of regulatory, strategic, and technological motivations. While the development follows multiple entry points across the cases, it converges towards a hybrid approach that closely aligns with Mintzberg’s (1987) notion of guided emergence, whereby strategy is intentionally directed by leadership while simultaneously evolving through learning and action across the organization. In terms of *data strategy constituents*, data strategies encompass value-focused visions and corresponding portfolios of data use cases and initiatives, complemented by governance, architecture, and cultural measures that establish foundational data capabilities. Most organizations define their data strategies at the group level, pursuing a dual rationale that mirrors the ambidextrous logic of defensively securing organizational control of data and offensively creating value with data. Depending on the organizational structure, this ambidexterity may be integrated into a centralized model or distributed into divisions, with defensive control remaining centralized at the group level. *Strategy implementation and impact* are mostly monitored using a combination of various progress metrics. Early strategic impacts are predominantly defensive, strengthening data governance and quality foundations that, in turn, enable subsequent value-creation efforts. Our findings highlight data strategy as an organization-wide and self-contained strategy, which is embedded in a broader *organizational strategy landscape*. Similar to IS strategies (Chen et al., 2010), data strategies exhibit strong linkages to business strategies, while also connecting to digital, technology-related strategies, and – in regulated industries – with risk, compliance, and security strategies.

By providing a conceptual framework for data strategy and empirical insights into its configuration in organizations, we advance IS literature as well as the emerging field of data studies (Aaltonen et al., 2021; Benfeldt & Persson, 2025). On the one hand, we anchor data strategy in the broader strategy discourse from management (Ronda-Pupo and Guerras-Martin, 2011; Mintzberg, 1987) and IS literature (Chen et al., 2010). We argue that data strategy encompasses not only data provision and governance, but also the organizational use of data, thereby serving as the conceptual foundation for analytics or AI (sub)strategies. On the other hand, we reinforce the perspective of data as a strategic resource, whose management requires comprehensive examination within the organizational context. This perspective elevates the prevailing discourse beyond tactical data management towards the strategic positioning of data as value-creating resources.

For practice, we provide in-depth empirical insights into the status of data strategies in mature European organizations. By capturing the executive-level perspective across diverse industries, our findings highlight that mature organizations consider data strategy a strategic imperative, with established governance structures and formal alignment mechanisms. The conceptual framework with four contextual elements of data strategy developed in this study, together with the empirical findings, can support practitioners in designing and evaluating their data strategy initiatives and aligning otherwise isolated approaches to data strategy development based on proprietary tools or methodologies.

Our study is not without limitations and opens up avenues for future research. While our case selection, focusing on European organizations with a comparatively high level of data maturity, enabled us to gain insights into data strategy as an institutionalized managerial practice, this may also include some bias. Consequently, we suggest broadening the scope to include a broader sample, including non-European companies, smaller and less mature organizations, as well as innovative companies that are increasingly centering their business models around data and AI to add further diversity and richness to the findings. Furthermore, our analysis is based on executive-level perspectives, while involving middle management representatives or data professionals could reveal additional company practices in the data strategy development process and their implementation. Finally, our study reveals the current state of data strategies in a rapidly evolving environment shaped by GenAI and agentic AI. As organizational AI adoption accelerates efforts to define, adapt, or extend data strategies, our conceptualization and the empirical findings offer promising avenues for future research, particularly in developing prescriptive guidance to support the effective design and implementation of data strategies.

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