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Beyond Digital Data and Information Technology: Conceptualizing Data-Driven Culture

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Abstract

Background: *The role of a data-driven culture in improving organizational performance is widely recognized, but its conceptual definition lacks uniformity, leading to the existence of various constructs. This paper proposes a guiding framework for a data-driven culture, aiming to foster a unified understanding that aids both researchers and practitioners in the information systems (IS) field.*

Method: *Adopting a qualitative research approach, this study conducts a systematic literature review to discern the breadth and depth of data-driven culture as portrayed in previous works. Alongside this, ten interviews were carried out with professionals well-versed in the application of data-driven strategies.*

Results: *The study uncovers the multifaceted nature of a data-driven culture, highlighting its influence on decision-making practices within organizations. It identifies a range of characteristics relevant to the construct and consolidates these into an integrative framework, thereby developing a conceptual definition for data-driven culture.*

Conclusion: *The paper contributes to the IS field by providing a framework that illuminates the concept of data-driven culture. This new understanding aids researchers in consistently theorizing the same phenomenon, supports the development of refined metrics for assessing data-driven culture, and paves the way for future research in this area. For practitioners, this framework delineates the characteristics of a data-driven culture and their interplay, enabling a more informed approach to cultural change efforts. Moreover, it highlights the importance of acknowledging the wider cultural context, and provides mechanisms to balance the emphasis on tools and values.*

Keywords: Data-driven Culture, Concept, Framework, Definition.

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Introduction

Data is the fuel and product of the digitized world (Thorp, 2012). Nowadays, businesses are leveraging the abundance of available data to enhance their value chain, either by refining existing products and services or creating new ones (Anton, Oesterreich, & Teuteberg, 2021). In this way, a data-driven business orientation can be crucial for promoting innovation and competitiveness in many sectors (Gupta & George, 2016; Upadhyay & Kumar, 2020). As emphasized by several industry surveys (Baier et al., 2022; LaValle et al., 2011), companies are aiming to cultivate a data-driven culture that encourages data-based decision-making and actions. In general, cultural forces within organizational boundaries can be a means to contribute to a company's effectiveness (Denison & Mishra, 1995; Iivari & Huisman, 2007) and the realization of its strategic objectives (Kaplan, 2011; Ye et al., 2008). More specifically, within a data-driven culture, empirical evidence indicates a positive correlation with business performance, as gauged by financial and market metrics (Anton, Oesterreich, & Teuteberg, 2021). However, a detailed examination of prior empirical work that operationalizes data-driven culture unveils a substantial disparity in its conceptual understanding. This diversity raises the question of whether the term "data-driven culture" carries a universal meaning across various researchers. The multifaceted nature of data-driven culture becomes apparent in the multitude of conceptual definitions spread across different research disciplines (Anderson, 2015; Gupta & George, 2016; Kiron et al., 2013; Medeiros & Maçada, 2022).

For example, several empirical studies exist that consider the concept of a data-driven culture as a prerequisite of technological compatibility for big data analytics (Chen et al., 2015) or as a means to foster relationships with the external organizational environment, i.e., customers, partners and suppliers (Shan et al., 2019). Such studies treat data-driven culture unidimensionally, incorporating it as a single facet of a latent construct. Conversely, others perceive data-driven culture as a formative construct, characterized by multiple dimensions and operationalized through several items. What they all have in common is that the authors conceptualize this form of organizational culture as a way of "how they do things", i.e., as a set of data- and analytics-related practices forming the backbone of decision-making. Yet, the scope of practices considered relevant to a data-driven culture varies considerably. Agyei-Owusu et al. (2021) contemplate data acquisition, Popovič et al. (2012) emphasize policy aspects, and Gupta and George (2016) regard workforce development as crucial facets of a data-driven culture.

Viewing data-driven culture as a manifestation of how that culture is used in practice aligns with Swidler's (1986) toolkit perspective. The perspective asserts that "culture independently influences action, but only by providing resources from which people can construct diverse lines of action" (Swidler, 1986, p. 273). In contrast, some prior research leans towards the collective meaning perspective, which posits that shared values shape collective action and organizational practices, as embodied in Behl's (2020) construct.

The construct of a data-driven culture, therefore, has been conceptualized heterogeneously and labeled variably, leading to a lack of clarity in its definition and the proliferation of constructs (i.e., varying names for constructs with overlapping conceptual domains (Bergkvist & Langner, 2019; Podsakoff et al., 2016)). This ambiguity and construct proliferation compromise nomological validity, obstruct knowledge accumulation, risk the construct being overlooked in literature reviews and meta-analyses, and create inconsistencies as some researchers use constructs interchangeably while others do not (Bergkvist & Langner, 2019; Podsakoff et al., 2016).

A clearer, more consistent understanding of the concept of a data-driven culture is required to tackle the prevalent conceptual pluralism and construct proliferation in the literature. Addressing this, Giorgi et al. (2015) provide an integrated framework that considers various perspectives to examine culture, including values, stories, frames, toolkits, and categories,

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and encourages scholars to appreciate these variations. This is in sync with Schein's (1991) emphasis on the importance of resolving conceptual pluralism in organizational culture, as he states, "[w]e cannot build a useful concept if we cannot agree on how to define it, 'measure' it, study it, and apply it in the real world of organizations" (p. 311). With data-driven culture being an emergent facet of organizational culture, it is imperative to adopt a structured framework, like the one proposed by Giorgi et al. (2015), to navigate the conceptual landscape effectively. Hence, the primary objective of this paper is to systematically develop a conceptual framework of data-driven culture to aid information systems (IS) researchers in consistently theorizing the same phenomenon. Establishing a common conceptual understanding represents a crucial initial step in construct development (Compeau et al., 2022; MacKenzie et al., 2011), an aspect often neglected or superficially addressed by positivist IS researchers (Pillet et al., 2022).

This study contributes to the IS field by addressing the ambiguous definition of "data-driven culture". By unifying theoretical perspectives and practical observations, we provide a robust understanding of the formation, evolution, and impact of a data-driven culture within organizations. We present an integrative framework and corresponding conceptualization, both of which serve as stepping stones for future research. Our efforts not only promote an investigation of this complex construct, but also offer a foundation for the development of refined, consistent metrics for evaluating data-driven culture.

Guided by Podsakoff et al.'s (2016) recommendations for developing robust conceptual definitions, we conducted a systematic literature review and ten interviews with IT professionals and industry experts to unearth potential characteristics associated with the concept under study. These identified characteristics are subsequently consolidated and organized into a framework and a definition for data-driven culture. Subsequently, we discuss our findings in relation to their research and practical implications, their limitations, and conclude with closing remarks.

Research Approach

In this study, we employed a qualitative research methodology to investigate the contemporary conceptualization and viewpoints of data-driven culture. As underscored by Myers (1997), qualitative research methodologies are particularly beneficial for examining social and cultural phenomena because they "help researchers understand people and the social and cultural contexts within which they live" (p. 241). Given our aspiration to augment comprehension of the term "data-driven culture" as a distinct social and cultural phenomenon, we identified a qualitative research methodology as optimally aligned with our research objectives. For this purpose, we followed the guidelines of Podsakoff et al. (2016), which describe several steps for generating robust theoretical conceptualizations. An overview of our research methodology is depicted in Figure 1.

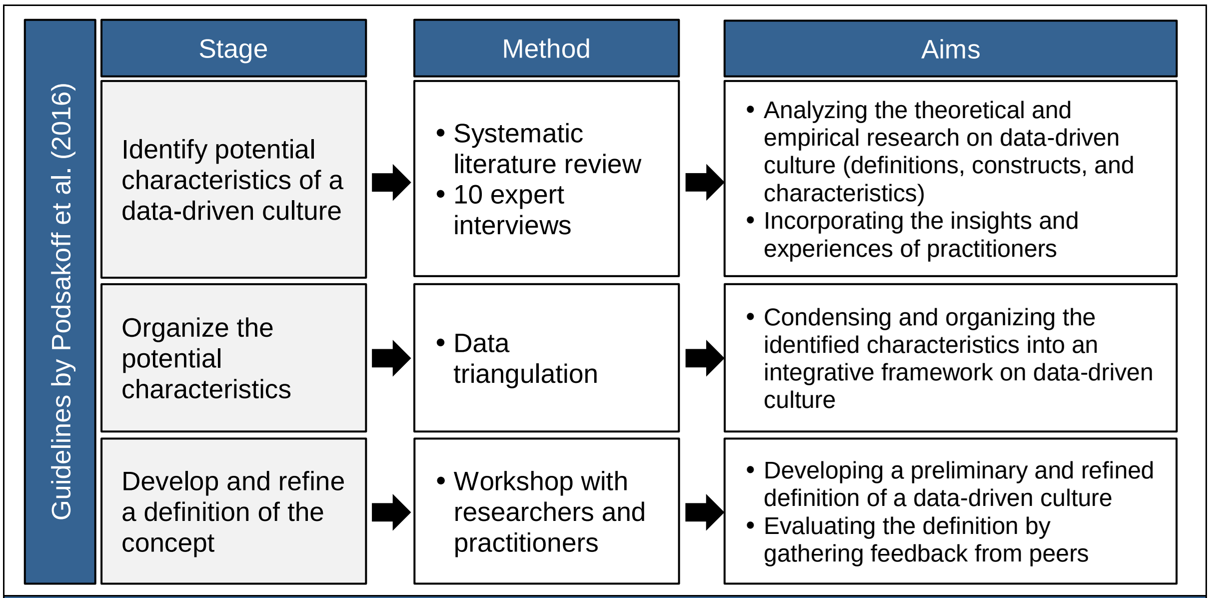

Figure 1 – Research Approach

Identifying potential characteristics of a data-driven culture. Podsakoff et al. (2016) define concepts as "cognitive symbols (or abstract terms) that specify the features, attributes, or characteristics of the phenomenon in the real or phenomenological world that they are meant to represent and that distinguish them from other related phenomena" (p. 161). Within the framework of abstracting a data-driven culture, the initial step involves broadly identifying the characteristics of the phenomenon. To this end, we conducted a systematic literature review, allowing for a thorough synthesis of findings from primary sources. Given our specific focus on a narrow set of questions (pertaining to data-driven culture), our exhaustive search strategy, and our overarching aim of integrating data from empirical sources, our literature review aligns with the definition of a qualitative systematic review as categorized by Paré et al. (2015). We executed our search strategy by conducting a systematic literature search, as prescribed by vom Brocke et al. (2009), during June and July 2022. To document and visually represent the outcomes of our literature search and selection process, we employed the PRISMA flow chart as suggested by Liberati et al. (2009). Hence, Figure 2 offers documentation, encompassing search protocols and detailed accounts of selection criteria, thereby enabling readers to assess the validity and thoroughness of our literature search and selection process.

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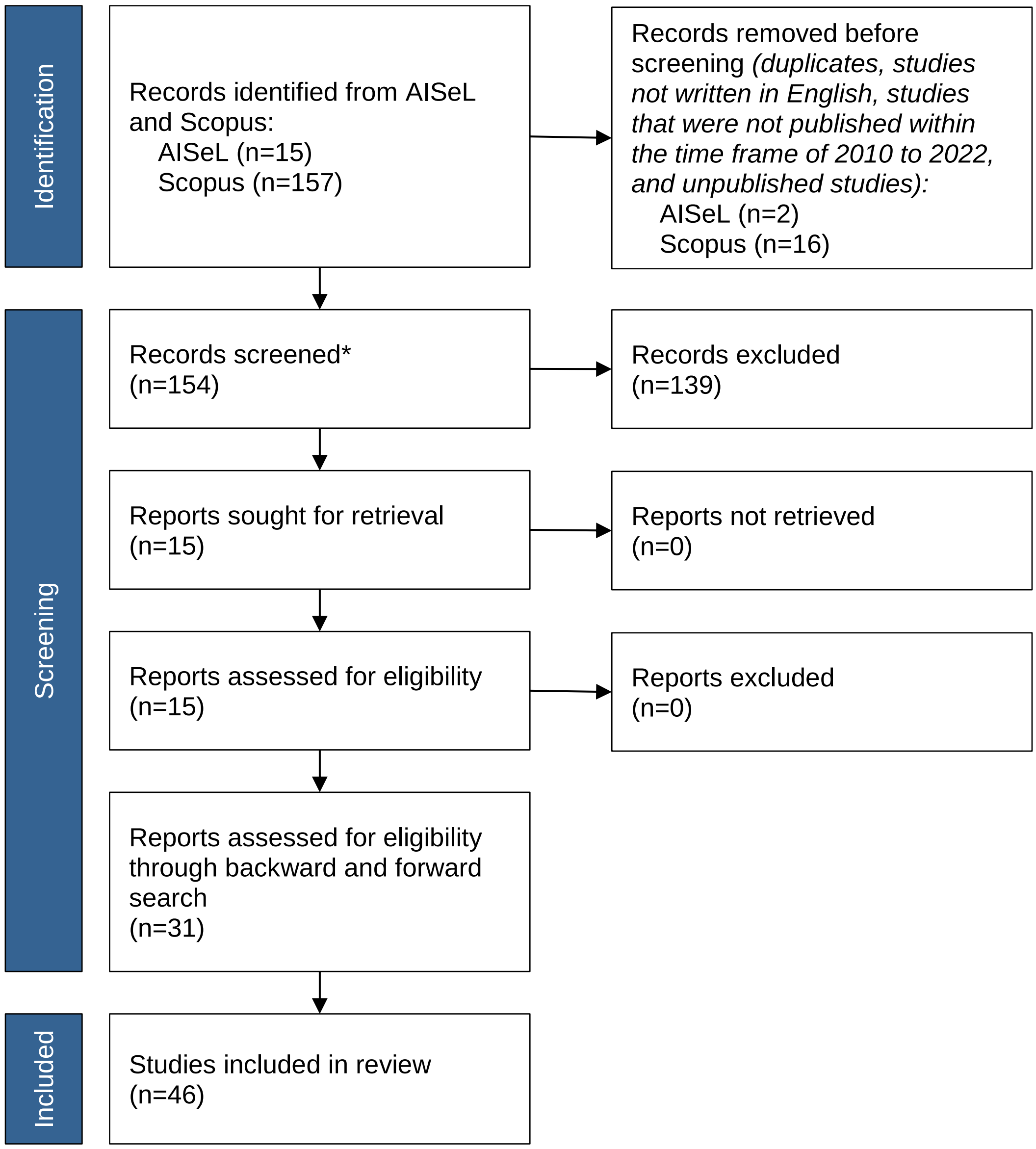
Search term in Scopus and AISeL:

"data driven culture" OR ("data driven" AND ("organizational culture" OR "corporate culture"))



*Inclusion criteria:
- Conceptual-type publications that specifically discuss the notion of a data-driven culture.
- Empirical studies that incorporate constructs where analytical and data-driven ideas are central to the research.

Exclusion criteria:
- Studies that do not have a conceptual or empirical focus on data-driven ideas and culture.
- Literature that is not written in English and was not published between 2010 and 2022.
- Unpublished studies, including working papers and dissertations.
- Duplicate studies that have already been included in the analysis.
- Bachelor's and master's theses or presentation slides that do not meet the criteria of the study.

Figure 2 – Literature Search and Selection Procedure

In the interdisciplinary database Scopus and the IS specific database AISeL, we applied the search terms *"data driven culture" OR ("data driven" AND ("organizational culture" OR "corporate culture"))* in titles, abstracts, and keywords. We defined these keywords after an iterative literature search process in which we attempted to verify as to which keywords lead to the most meaningful results. These keywords were deemed relevant to our study, as they facilitated the identification of both conceptual and empirical studies explicitly addressing data-driven culture within an organizational context. Keywords leading to articles where data-driven culture was merely part of a theoretical backdrop or discussion were excluded, as these did not contribute to the identification of pertinent primary studies.

The initial search utilizing the chosen keywords yielded 15 results in AISeL and 157 in Scopus. We restricted our search to publications in English, encompassing a wide array of material, including research articles, practical reports, conference papers, and books that either applied constructs of data-driven culture in empirical research or theorized about the concept. Recognizing that data-driven culture has gained relevance in recent years due to the surge in big data analytics and artificial intelligence (AI) (AL-Ma'aitah, 2020; Anton, Oesterreich, & Teuteberg, 2021; Enholm et al., 2021; Mikalef et al., 2018; Pai & Chandra, 2022; Radhakrishnan et al., 2022), we further refined our search to publications from the period of 2010 to 2022. This refined search led to the identification of 46 papers, which we subsequently scrutinized in full text for further analyses (refer to Appendix A for a comprehensive overview of the included studies and selected descriptive statistics such as number of studies per year, publication type, and publication outlet).

To bolster the comprehension of the concept pertaining to data-driven culture, we conducted ten semi-structured interviews with industry experts who specialize in data-driven and analytical practices within the e-commerce and consulting sectors. These experts possess extensive experience in adopting and implementing analytics technologies, as well as in establishing the necessary organizational conditions to support such endeavors. In order to capture multifaceted perspectives, we deliberately selected experts from various hierarchical levels and professional backgrounds. Table 1 provides an overview of the ten interviewees. The interview guideline was developed based on Mayring's (2002) recommendations for subject-oriented procedures. We conducted semi-structured interviews to allow for subjective perspectives while still allowing for comparable statements. The guiding questions were based on the stages for good conceptualizations by Podsakoff et al. (2016). For the transcription, we followed the guidelines provided by Dresing and Pehl (2013).

Table 1 – Overview of Conducted Interviews

Interview	Position	Industry	Interview duration
P1	Software architect	Marketing	33 min
P2	Business consultant	E-Commerce	44 min
P3	Chief operating officer	E-Commerce	37 min
P4	Data analyst and researcher	Management consulting	40 min
P5	Business consultant	E-commerce	38 min
P6	Business consultant	IT consulting	45 min
P7	Business consultant	IT consulting	33 min
P8	Service designer	IT Services in the financial sector	35 min
P9	Application consultant	E-commerce	41 min
P10	IT consultant	IT consulting	50 min

For data analysis, we adopted a hybrid coding strategy, blending deductive and inductive elements (Bandara et al., 2015). The coding was conducted for both the interview data and the literature data.

The deductive coding scheme was intricately structured around the first stage of Podsakoff et al.'s (2016) framework, which advocates for the identification of a concept's potential characteristics as a critical foundation in conceptual definition development. In light of this, our deductive coding scheme embraced the following categories: (1) Definition of Data-Driven

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Culture, designed to capture existing definitions; (2) Data-Driven Culture Construct, to investigate the underlying structure of the concept; (3) Characteristics of a Data-Driven Culture, to directly align with Podsakoff et al.'s first stage by pinpointing key features and attributes. Additionally, we extended the scope to encompass (4) Impact of Data-Driven Culture on Organizational Performance, in order to gauge the real-world effects of embracing a data-driven culture; (5) Challenges in Developing a Data-Driven Culture, to unearth any potential hurdles; and (6) Best Practices for Cultivating a Data-Driven Culture, to provide actionable insights rooted in the concept's attributes.

The inductive component of our coding strategy ensured flexibility, allowing us to detect and code emergent themes. For instance, within the "Characteristics of a Data-Driven Culture" category, inductive coding facilitated the identification of more detailed sub-themes, such as "Organizational Factors", "Technical Factors", and "Human Factors", which are integral components of data-driven culture. Through this hybrid coding strategy, we achieved a thorough, well-structured identification and organization of data-driven culture's core elements.

The coding procedure was undertaken independently by two researchers, consistent with the interrater agreement (IRA) principle to maintain uniformity in the rating process (LeBreton & Senter, 2008). The IRA metric evaluates the degree of consistency amongst various raters independently assessing the same set of items (LeBreton & Senter, 2008), thereby fortifying the objectivity and validity of our results. Collectively, we attained a satisfactory agreement level (Cohen's Kappa) of 0.79. Instances of discord were resolved through conclusive discussions amongst the coders until a consensus was achieved.

Organizing the potential characteristics. For the next step, we used a triangulation approach in order to examine the research question from multiple perspectives and create a more holistic understanding of the concept. The results from both methods were merged, organized and summarized in an explanatory model by linking the characteristics of data-driven culture with the dimensions of Giorgi et al.'s (2015) integrative framework on organizational culture.

Developing a definition on the concept. Based on the explanatory model of an integrative framework on data-driven culture and considerations regarding necessary and sufficient characteristics, we derived a conceptual definition of a data-driven culture. We conducted a workshop in November 2022 with IS researchers and practitioners to explain and discuss the definition in an attempt to clarify ambiguities and refine phrasing.

Data-driven Culture: Definitions, Constructs and Characteristics

Definitions and Constructs

The digital revolution influences organizational cultures by reshaping social interactions and cultural aspects while bringing forth technologies as a means to manage these changing norms, behaviors, and beliefs (Grover et al., 2022; Miller, 2020). With the abundance of data and the growing significance of data-driven decision-making in digital business strategies, the concept of data-driven culture has gained prominence, specifically in relation to fostering the adoption of technologies such as big data analytics and AI (Anton, Oesterreich, & Teuteberg, 2021; Enholm et al., 2021; Mikalef et al., 2018). Therefore, a data-driven culture represents a specialized organizational culture wherein organizations prioritize data as a foundation for decision-making processes (Kremser & Brunauer, 2019).

Data-driven culture must be distinguished ontologically from the related concepts *IT culture* and *digital culture*. While all three concepts involve technological resources like data and information systems within a value-creating system, there are significant differences in terms of their outcome perspectives. The desired outcome of an IT culture primarily revolves around traditional value objects such as physical products and more efficient production processes. In contrast, a digital culture emphasizes digital value objects like apps, platforms, and digital practices (Grover et al., 2022). On the other hand, a data-driven culture places its focus on information, which serves as a foundation for informed decision-making (Kiron et al., 2013). This emphasis on utilizing information can lead to additional value-adding mechanisms that ultimately impact business performance (Anton, Oesterreich, & Teuteberg, 2021; Oesterreich, Anton, & Teuteberg, 2022; Oesterreich, Anton, Teuteberg, & Dwivedi, 2022).

Previous research has investigated data-driven culture from various perspectives, encompassing a multiplicity of viewpoints. To emphasize this diversity, we have deliberately chosen definitions in Table 2 that reflect different viewpoints on the concept. For instance, Berndtsson et al. (2018) emphasize experimentation and learning, while Anderson (2015) focuses on data access and quality. These definitions also reflect the toolkit and collective meaning perspectives. Kirson et al. (2013) allude to the collective meaning perspective, suggesting a shared belief among stakeholders, which aligns with Davenport et al. (2001) view that data and information should be an intrinsic part of an organization's value system. In contrast, Gupta and George (2016) adopt the toolkit perspective, considering culture as a set of human resources making decisions based on data insights.

Table 2 – Definitions of Data-driven Culture

Definition	Reference
A true data-driven organization is a data democracy and has a large number of stakeholders who are vested in data, data quality, and the best use of data to make fact-based decisions and to leverage data for competitive advantage	Anderson (2015)
A data-driven culture is characterized by a decision process that emphasize testing and experimentation, where data outweighs opinions, and where failure is accepted –as long as something is learnt from it	Berndtsson et al. (2018, pp. 1-2)
… the extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data	Gupta & George (2016)
… a pattern of behaviors and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a critical role in the success of their organization	Kiron et al. (2013, p. 18)
The DDC [data-driven culture] refers to organizational norms, values and behavioral patterns, resulting in systematic ways to create, gather, consolidate, analyze the data and make it available to the right public, which includes the extension of the use of these data for making from business decisions and management support to analysis, receptivity to learn and disseminate knowledge, as well as an inclination to change and improve ways of working and making data-driven decisions	Medeiros & Maçada (2022, p. 956)

Apart from these differing definitions, the conceptual heterogeneity of the data-driven culture term and construct proliferation is also reflected in the operationalization of the constructs in empirical studies. Table 3 offers an overview of the various multi-item constructs that focus on organizational cultures in which analytic and data-driven ideas are salient.

Consequently, there exists a significant level of conceptual heterogeneity not only in the conceptual definitions (refer to Table 2) but also in how the construct is measured and assessed in empirical research (refer to Table 3). This lack of consistency hinders a common understanding of data-driven culture in both theoretical and practical contexts.

Table 3 – Overview of Constructs of Data-driven Culture (and Related Concepts)

Construct	Items	Reference
Data-driven culture	(1) Our organization has the data it needs to make decisions; (2) Our organization depends on data to support its decision-making; (3) Our organization spends significant time analyzing data to support decision-making; (4) Our organization uses data rather than guess work to make decisions	Agyei-Owusu et al. (2021)
	(1) Organizational strategy; (2) Organizational policy and rules; (3) Organizational structure; (4) Business process; (5) Prioritizing BA investments	Cao & Duan (2014)
	(1) We believe that having, understanding and using data and information plays a critical role; (2) We are open to new ideas and approaches that challenge current practices on the basis of new information; (3) We depend on data-based insights to support decision-making; (4) We use data-based insights for the creation of new services or products; (5) Individuals have need for data to make decisions	Cao & Duan (2015); Duan & Cao (2015); Duan et al. (2020); Medeiros & Maçada (2022)
	(1) I believe decisions should be based on available information coming from a BA solution; (2) Our firm has a practice of decision-making based on available data; (3) Data plays an important role in new product development; (4) Data plays an important role in process improvement	Chatterjee et al. (2021)
	(1) We consider data as an asset; (2) We base most decisions on data rather than instinct; (3) We are willing to override our intuition when data contradict our viewpoints; (4) We continuously assess our strategies and take corrective action in response to the insights obtained from data; (5) We continuously coach our people to make their decisions based on data	Dubey et al. (2018); Gupta & George (2016); Mikalef et al. (2018); Mikalef et al. (2019)*; Mikalef, Pappas et al. (2020); Mikalef & Krogstie (2020)*
Related constructs		
Analytical decision-making culture	(1) The decision-making process is well established and known to its stakeholders; (2) It is our organization's policy to incorporate available information within any decision-making process; (3) We consider the information provided regardless of the type of decision to be taken	Popovič et al. (2012)
BI&A culture	(1) Employees understand the importance of BI for the success of the organization; (2) Employees are encouraged for intelligence exploration and experimentation; (3) Senior management support the role of BI&A in our firm's success; (4) My organization expects a high level of participation in intelligence capture, share, and transfer; (5) My organizations have an underlying value of on-job training and learning around BI&A; (6) In my organization, the vision and objective around BI&A are clearly stated and understood	Ramakrishnan et al. (2020)
Big data-driven culture	(1) We consider data as an asset; (2) We base most decisions on data rather than instinct; (3) We are willing to override our intuition when data contradict our viewpoints; (4) We continuously assess our strategies and take corrective action in response to the insights obtained from data; (5) We continuously coach our people to make their decisions based on data	Yu et al. (2021)

Table 3 – Overview of Constructs of Data-driven Culture (and Related Concepts)

Construct	Items	Reference
Data-driven decision (one dimension of the organizational culture construct)	(1) The organization has an analytics wing; (2) Organizations' have implemented ERP; (3) We are well convergent with the ERP; (4) Our organization takes a decision based on the proper analysis of data.	Upadhyay & Kumar (2020)
Organizational culture of big data	(1) Our decisions are based on data; (2) A dependency on hunches for decision-making is strongly discouraged in our organization; (3) Depending on data is part of our organization routine; (4) We have culture of data driven work; (5) Our executive use lots of data to justify decisions they have already taken through traditional approaches	Shamim et al. (2019)
*Only a subset of the items was used to operationalize the construct.		

Characteristics of a Data-driven Culture

Research that addresses data-driven culture often adopts the resource-based view (RBV) of the firm (Anton, Oesterreich, & Teuteberg, 2021; Gupta & George, 2016; Krishnamoorthi & Mathew, 2018), which posits that an organization's resources and capabilities are the primary drivers of its business value and competitive advantage (Bharadwaj, 2000; Drnevich & Croson, 2013). These resources can include tangible assets such as financial resources, physical assets, and technology, as well as intangible assets such as organizational culture. In this context a data-driven culture can be considered as a valuable organizational resource that impacts business value on the operative, financial, or market dimension (Anton, Oesterreich, & Teuteberg, 2021). However, as Melville et al. (2004) emphasize, a resource is only valuable when used effectively in a business context along with other human, technical, and organizational resources. Our analyses confirm this complementary nature, revealing that a data-driven culture is closely linked to or characterized by other tangible and intangible aspects with the objective of delivering business value. We use the dimensions of *business value, human resources, technical resources, and organizational resources* to report on our findings from the literature review and expert interviews.

Business Value

A data-driven culture is based on the principle that decisions in a company are reached on the basis of data. This is a common theme in almost all empirical and theoretical work that addresses the subject (e.g., Anderson, 2015; Chatterjee et al., 2021; Mikalef et al., 2018; Mikalef, Krogstie et al., 2020; Yu et al., 2021). Organizations with a data-driven culture tend to benefit from more informed and accurate decisions based on objective facts and evidence, rather than guesswork or assumptions (Gupta & George, 2016; Mikalef et al., 2018; Oesterreich, Anton, & Teuteberg, 2022). Similarly, practitioner P4 refers to the culture in his/her company as data-driven because his/her consultancy firm "*tries to make decisions based solely on data and not on gut feeling*". According to P6, this aids an organization in *"making more informed and focused decisions and allows businesses to identify new opportunities and avoid potential threats*." Practitioner P9 adds that fact-based decision-making must occur at all levels of the hierarchy. Gupta and George (2016) concur by emphasizing that these types of decisions need to permeate through the various stakeholders such as executives as well as lower level employees. This can nurture an environment of constant experimentation and learning (Mikalef et al., 2019; Storm & Borgman, 2020). By regularly collecting and analyzing data, companies can identify trends, patterns, and insights that help them make decisions and support their initiatives. By staying ahead of the curve and adapting to changing market conditions, organizations can measure, track and thus improve

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their performance, identify strengths and weaknesses and ultimately make data-driven improvements. This is expressed in optimized operations and business processes (Chatterjee et al., 2021) and innovation in the form of new or improved services and products (Anton, Oesterreich, Schuir et al., 2021; Duan et al., 2020; Medeiros & Maçada, 2022; Mikalef & Krogstie, 2020).

Human Resources

A data-driven organization is characterized by a workforce that is data literate and engages in data democracy (P6). Data democracy requires employees to be "vested in data, data quality, and the best use of data" (Anderson, 2015). Thus, employees of a data-driven organization should be empowered to share data with others, embrace it, and understand the importance of it (Berntsson Svensson & Taghavianfar, 2020). Jesenko and Thalmann (2023) in this context, underscore the importance of this ethos being deeply embedded within the employees' mindset. This can be approached through appropriate recruitment or educational efforts to create awareness and understanding among an organization's workforce about the value of data as an asset and its impact on the business (Holsapple et al., 2014; Visvizi et al., 2022). According to several practitioners, in addition to awareness, a data-driven culture also constitutes training the workforce in the necessary skills in data management and the use of analytics tools (P1, P2, P3, P6), which also requires willingness to learn and experiment (P6). In addition, many empirical studies attribute significant importance to coaching and training of employees in the context of a data-driven culture (Dubey et al., 2018; Gupta & George, 2016; Mikalef et al., 2018; Mikalef, Krogstie et al., 2020). Establishing a workforce that is data literate and aware of the explanatory value of the data can foster norms, values and behaviors "in which evidence-based problem solving (and recognition) is of high priority" (Holsapple et al., 2014).

Technical Resources

Data-driven organizations must develop a systematic approach to create, collect, and consolidate data (Medeiros & Maçada, 2022). Therefore, it is necessary to establish an infrastructural framework that supports both data operations (integration and management of data) and data processing (tools, software, algorithms) (Oesterreich et al., 2021). As the concept of data-driven culture is increasingly invoked in the context of big data (analytics) and AI (AL-Ma'aitah, 2020; Anton, Oesterreich, & Teuteberg, 2021; Enholm et al., 2021; Mikalef et al., 2018; Yu et al., 2022), related data management and technologies such as data lakes and distributed systems receive more attention (Kloeckner et al., 2018; Oesterreich et al., 2021). However, data-driven organizations do not necessarily need to experiment with big data, rather they are characterized by their ability to capture and use their data base in a systemic way, for example via BI-solutions (Ramakrishnan et al., 2020) or SAP systems (Shao et al., 2022; Upadhyay & Kumar, 2020). However, research and interviews with practitioners indicate that experimentation with and use of advanced analytics technologies and tools for data operations and processing is a beneficial aspect for establishing a data-driven culture, as organizations explore their data foundation and seek ways to leverage it (P2, P4, P5, P6).

In addition, practitioner P9 highlights that a data-driven organization *"accesses and leverages different types of data, both qualitative and quantitative, from internal as well as external sources"*. This should not only apply to organizational silos, but to the entire organization (Hannila et al., 2022). Therefore, organizations should provide every employee the opportunity to access data independently (P4). For example, Kloeckner et al. (2018) suggest to promote data access via dashboards and self-service analytics. Most research substantiates the importance of the availability of and access to data (e.g., Anderson, 2015; Duan et al., 2020; Holsapple et al., 2014; Medeiros & Maçada, 2022). Nevertheless, accumulation of and access to data are no guarantee of data quality. Practitioner P10 points out that "*data quality is of course the most important thing*". According to practitioner P8, an organization with a data-driven culture needs to ensure consistency, completeness, correctness, and integrity of its data. Only in this way, decisions can be reliable.

Organizational Resources

Top management must enable building a data-driven culture and actively participate in discussions on the topic to avoid segregated departments and inflated expectations (Berndtsson et al., 2020). It is important for leaders to be open to and encourage data-driven insights among colleagues and subordinates, or even demand data-driven decision-making from their employees (Windt et al., 2019). From a structural perspective, companies also need to adopt a long-term strategy to operationalize the desired culture and create the conditions for it, for example, by creating positions such as chief data officers and centralized functional units for analytics, standardized reports, and data queries (Berndtsson et al., 2020). According to P10, other efforts include digitizing processes to drive data collection within the organization. For P9, this also includes the definition and regular use of KPIs for business management. P6 adds to this component by highlighting the importance of establishing policies for data governance and emphasizing the importance of internal corporate communications. If such transformations are to be made in existing organizational structures, this also requires the will within a company to go along with and accept such changes, which must be supported by change management measures (Behl, 2020; Pethig, 2018).

An Integrative Framework on Data-driven Culture

The aforementioned section delineated the characteristics pertaining to business value, human resources, technical resources, and organizational resources, which are intricately linked to a data-driven culture. This characteristic pool encompasses various values, tools, and measures that are associated with a data-driven culture (a summary of this characteristic pool is provided in Appendix B). While there are recurring patterns and overlaps between the experts' statements and the literature, it is becoming evident that there is no consensus on which of the characteristics mentioned are necessary and sufficient. Rather, our results show that a data-driven culture is neither static nor always based on the same characteristics. Take the example of the attribute "availability of data," which can be a characteristic of a data-driven culture, but is not inherently a sufficient condition for the formation of the culture. Data availability certainly is an important and necessary factor in the process of accessing and using the data needed for decision-making. However, it is possible for an organization to have a data-driven culture even if the data is not always readily available. For example, an organization may have a strong culture of using data to make decisions, but may need to invest in new technologies or processes to access and use the data it needs. On the other hand, an organization may have access to a large amount of data but not necessarily have a strong culture of using data for decision-making. The same is true for the characteristic "use of analytical tools". For example, an organization may have an environment in which the use of data for decision-making is firmly embedded, but may not necessarily use specific analytical tools or technologies to do so. Conversely, an organization can use analytics tools and technologies without necessarily having a strong culture of using data to inform decision-making. Hence, it is not prudent to rely solely on specific characteristics when conceptualizing a data-driven culture, as none of the individual characteristics from the pool can be considered a sufficient condition on its own.

Previous IS research has predominantly examined culture theory through a value-based approach, with a specific emphasis on exploring the relationship between IT use and culture (Leidner & Kayworth, 2006). A value-based approach centers on the collective meaning perspective, which assumes a causal direction starting from norms and values to actions and behaviors. However, contemporary research, such as Giorgi et al. (2015) and Grover et al. (2022), points to "think[ing] of culture more dynamically and offer[ing] an alternative metaphor,

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that of a swinging pendulum that moves between a value-based and a toolkit-based cultural model" (Giorgi et al., 2015, p. 21). In fact, there are also views that locate the origins of organizational cultures in the use of tools such as AI technologies (Enholm et al., 2021) or business analytics (Chatterjee et al., 2021) to increase innovation capability and thus to lastingly shape and change corporate cultures. The findings of the previous section support such a dynamic perspective entailing a pool of values, practices and knowledge that form a data-driven culture. Thus, we employ the dynamic framework on culture of Giorgi et al. (2015) to categorize and condense the findings from Stage 1 (cf. Figure 2). This framework provides *categories*, *frames,* and *stories* as mechanisms "that operate within broader systems of culture as values and toolkit, expressing and diffusing commitments and beliefs among actors" (Giorgi et al., 2015, p. 22). In this way, a framework is provided that makes the dynamic and complex character of the mechanisms of a data-driven culture more tangible without specifying a set of discrete characteristics that always form a data-driven culture by themselves.

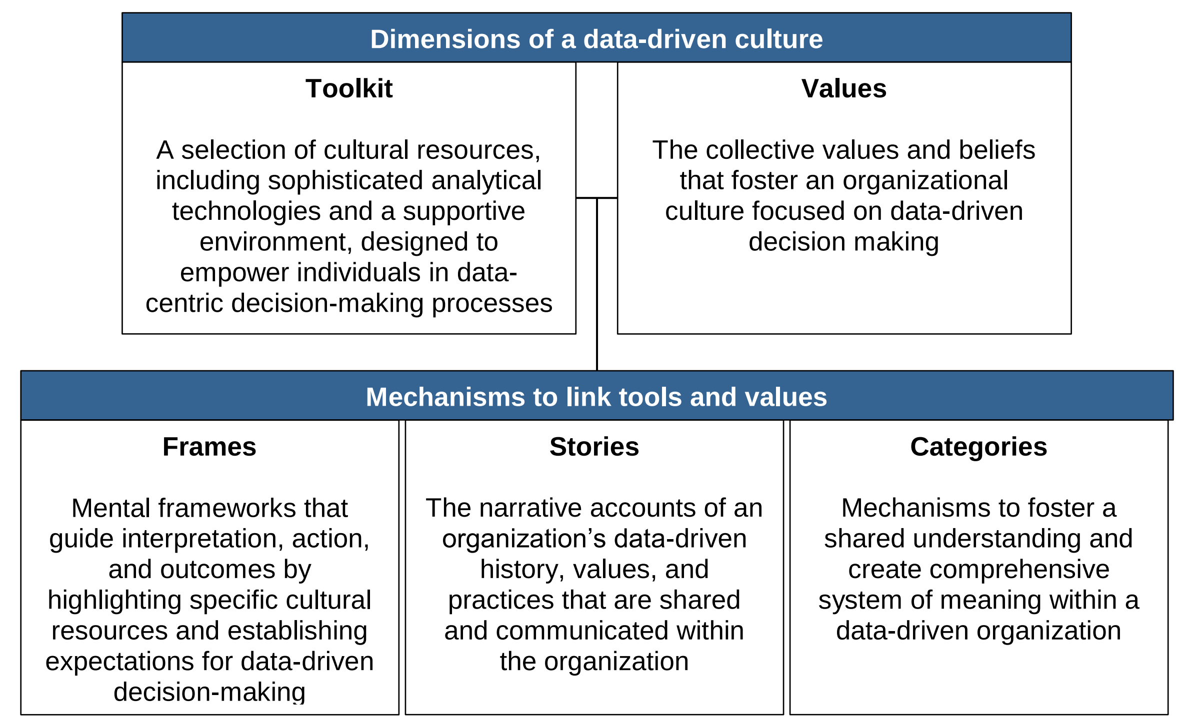

Figure 3 – Integrative Framework on Data-driven Culture (Adapted from Giorgi et al., 2015)

Dimensions and Mechanisms of the Framework

According to a widely accepted conceptualization, culture is often defined by the presence of shared values among a group of individuals (Leidner & Kayworth, 2006). However, the development of culture and its associated values is not uniform for every individual. Straub et al. (2002) draw upon the social identity theory to illustrate that individuals are influenced by various subcultures based on their national, organizational, or ethnic backgrounds. Nonetheless, within the confines of an organization, individuals may subscribe to shared values that define social norms, thereby creating a framework for behaviors and communication (Leidner & Kayworth, 2006). The **values** dimension in our proposed framework revolves around the shared values and beliefs that underpin the organization's culture concerning data and decision-making. This includes the importance of basing decisions on facts and evidence, the need for transparency and honesty in data handling, and the belief that informed decision-making should be applied across the organization. This also entails the importance of creating awareness and understanding among the workforce about the value of data and its impact on the business. However, it is worth noting that there are critiques regarding the predictive power of values in influencing behavior and outcomes (Giorgi et al., 2015). Swidler (1986) provides an illustrative example of individuals in poverty, who, despite sharing middle-class values regarding the importance of obtaining a good education, are unable to achieve it. This instance underscores the fallacy of the presumption that individuals' actions are dictated exclusively by their interests or values. Rather, it emphasizes the complex interplay of actions within a cultural repertoire.

Within an organizational context, individuals have the ability to engage with a rich cultural repertoire, strategically utilizing distinct cultural resources to influence and guide their actions. By invoking these cultural resources, individuals are empowered to draw upon the organization's collective body of knowledge, values, and practices, using them as a compass for their decision-making and action-taking processes (Weber, 2005). Different configurations of cultural resources can be utilized depending on the nature of the problem and individuals' capabilities, aiding in solving the task at hand (DiMaggio, 1997). This dynamic interaction is encapsulated within the **toolkit** dimension of our proposed framework. This dimension envelops an array of cultural resources, which range from an environment fostering the use of advanced analytical technologies and tools for data operation and processing, to a supportive organizational milieu that attracts and nurtures talent equipped with the necessary skills and training for effective tool utilization. Cultivating such a "toolkit" is a crucial aspect of the framework, enabling individuals to fully harness the potential of data-driven decision-making.

It is important to reiterate that the dynamic interplay between tools and values is essential in shaping a data-driven culture, as highlighted by the practical insights of Díaz et al. (2018): "Get data in front of people and they get excited. But building cool experiments or imposing tools top-down doesn't cut it. To create a competitive advantage, stimulate demand for data from the grass roots" (p. 6). Although data availability, tools, and experimental environments provide invaluable cultural resources to support individuals in their practices and lay the groundwork for data-driven decision-making, these findings stress the necessity of harmonizing these resources with foundational values to actualize this course.

Our proposed framework incorporates mechanisms that establish connections between tools and values (Giorgi et al., 2015). These mechanisms play a crucial role in focusing and orchestrating the plethora of cultural resources within organizations, enabling a specific course of action to be pursued (Leonardi, 2011). Among these mechanisms, **frames** serve as mental frameworks or perspectives utilized by organizations to shape meaning, actions, and outcomes (Leonardi, 2011). Previous research demonstrated the explanatory power of frames. For instance, Orlikowski and Gash (1994) used frames to convey priorities, resources, management motivation, and features during the adoption of Lotus Notes software. Similarly, Davidson et al. (2002) employed the technology frame as a socio-cognitive mechanism to influence sensemaking during the requirements determination processes, exemplifying how frames can impact organizational activities. Within a data-driven culture, frames spotlight specific cultural resources, encapsulating an assortment of assumptions, knowledge, and expectations relevant to data-driven decision-making. By amplifying the prominence of these resources, frames can foster an environment that stimulates employees' curiosity, encourages experimentation, and facilitates the adoption of tools for data analytics or AI. The frames are often implicitly embedded in the priorities outlined in data governance policies, internal and external corporate communications, and demonstrated commitments from top management.

A further mechanism employed for instilling values and tools within an organization is the use of **stories**. At a macro-level, stories effectively encode metanarratives, such as the concept of American hardworking meritocracy, and weave them into the fabric of the organizational culture, thereby influencing the beliefs and actions of employees (Giorgi et al., 2015). These stories serve as a means to make sense of one's social context and typically follow a narrative structure with a beginning, middle, and end, comprising causally connected sequences of events. They are often captivating as they evoke emotions and tap into shared experiences (Small et al., 2010). Within our framework, stories are tasked with narrating the evolution of an organization's data-driven culture, including the leveraging of data for innovative products and services, along with requisite recruitment or educational initiatives to foster comprehension and appreciation of data's value among the workforce. These narratives are disseminated in a variety of ways, such as in mission statements or company profiles.

The final mechanism in our framework incorporates **categories**, which "mediate perceptions by furnishing understandings about the attributes and behaviors that are expected of particular 'types' of organizations" (Wry et al., 2014, p. 1311). Past organizational research suggests that such categorization can impact employees' alignment with specific strategic directions. Absence of a well-defined position within a market segment or field can precipitate issues, including employee disengagement (Zuckerman, 1999) and legitimacy concerns (Greenwood et al., 2002). Conversely, Grover et al. (2018) discuss the signaling effects of clearly defining an organization's stance within the sphere of big data initiatives. This strategic positioning not only serves as an emblem of innovation within organizations, but also bolsters their reputation. The resultant enhancement in organizational standing could foster stronger identification with the organization among employees. Hence, categories facilitate the positioning of entities within a comprehensive system of meaning (Giorgi et al., 2015). This applies not only externally in relation to the market, but also internally, providing a clear structural and strategic orientation within the organization itself. In the context of a data-driven organization, where roles often span data-focused tasks and broader business-related duties, achieving alignment becomes paramount (Waller, 2020). Establishing a shared reference point is vital in harmonizing and bridging the divide between business and technical data roles, given the interdependence of their expertise and collaborative efforts (Anton et al., 2020).

Defining a Data-driven Culture

The integrative framework emphasizes that the concept of a data-driven culture is dynamic and not confined to static characteristics. Instead, it is viewed as a complex system that involves a combination of values and tools, conveyed through various mechanisms that cannot be solely attributed to specific individual characteristics or linear cause-effect relationships. Furthermore, different configurations of mechanisms manifesting values and tools can lead to the same outcome, which reflects the equifinality assumption of many configurational theories, stating that there are "feasible set[s] of equally effective, internally consistent patterns of context and structure" (Van de Ven & Drazin, 1984, p. 335). Therefore, we argue that a data-driven culture is characterized by shared values and beliefs around data as the basis for decision-making, as well as an environment that embraces data-driven practices and provides the necessary tools and resources to enable data-driven decisions. The value and toolkit dimensions are linked by configurations of:

- Frames, i.e., mental models and frameworks that guide interpretation, action, and outcomes by highlighting specific cultural resources and establishing expectations,
- Stories, i.e., an organization's data-driven history, values, and practices that are shared and communicated within the organization, and
- Categories, i.e., mechanisms to foster a shared understanding and create a comprehensive system of meaning within a data-driven organization.

Our interpretation of a data-driven culture diverges from prior or associated interpretations. These are typically predicated on either a value-oriented (Abhari et al., 2021; Koch et al., 2013; Medeiros & Maçada, 2022) or a toolkit-centric approach (Gupta & George, 2016). Such perspectives, however, allow for only one causal trajectory, occasionally incorporating individual-specific characteristics which may not suffice to manifest a robust data-driven culture. For example, Kiron et al. (2013) posits that the mere presence, comprehension, and utilization of data is adequate to develop a data-driven culture. In contrast, our definition integrates the dual facets of values and tools, and further enriches them with a configurational principle underpinning their manifestation.

Consequently, our conception of a data-driven culture should not be confined to specific characteristics or perspectives. Rather, it should present a dynamic framework that integrates values and cultural resources. This framework illuminates the fundamental constituents and pathways but also recognizes the distinctiveness of each organization, emanating from unique configurations.

Discussion

The motivation for this study arises from the lack of theoretical and practical consensus on the definition of a data-driven culture, which has resulted in conceptual heterogeneity and construct proliferation. By carrying out a systematic literature review and engaging in expert interviews, we have identified a set of common and recurring characteristics associated with the concept. Data-driven culture is understood as an organization's reliance on data to make decisions and drive business value. This particular form of an organizational culture is often interconnected with various tangible and intangible resources, including human, technical, and organizational resources. In a data-driven culture, employees possess data literacy and actively participate in data democracy, which entails being empowered to share and effectively use data. Technical resources encompass data infrastructure, tools, and processes for data collection, storage, and analysis, while organizational resources include corporate leadership, governance, and strategies for leveraging data to create business value. While these identified tangible and intangible resources are important within the context of a data-driven culture, they alone are not sufficient to ensure that an organization truly embodies a data-driven approach.

Building upon these insights, we propose a conceptualization of data-driven culture that combines the collective meaning perspective and the toolkit perspective, in response to the growing call for the integration of these two common approaches to cultural concepts (Giorgi et al., 2015; Grover et al., 2022). This integrated theoretical perspective on data-driven culture provides novel opportunities for an exploration of the concept. It allows for a deeper understanding of how culture spreads within an organization and the mechanisms involved in the emergence of a data-driven culture (Giorgi et al., 2015). This enhanced understanding can inform theoretical and empirical research on data-driven culture and facilitate its operationalization. Additionally, it can support the development of interventions aimed at promoting the adoption and implementation of data-driven practices within organizations.

Theoretical Implications and Avenues for Future Research

Based on our analysis of research on data-driven culture, we present four promising directions for future research in the field of IS. These research avenues offer directions that have the potential to enhance the scholarly discourse within the IS community. A summary of these future research avenues can be found in Table 4.

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Table 4 – Summary of Research Directions

Research Direction	Description
Organizational practices and the evolution of data-driven culture	Examine the dynamic interplay between organizational practices (e.g., the adoption of big data analytics and AI) and the evolution of a data-driven culture, considering how cultural resources and values co-evolve within the organizational context.
Quantifying data-driven culture	Given the complexity of accurately quantifying a data-driven culture, when formulating metrics in this context, prioritize the creation of tangible measurements focused on the cultural resources embedded within an organization's cultural repertoire.
The complexity of cause-and-effect	Use comprehensive methods like qualitative comparative analysis to explore the complex cause-and-effect relationships in data-driven culture, acknowledging the concept of equifinality (multiple paths leading to the same outcome).
Interpretivist methodologies	Employ interpretivist methodologies like ethnographies to explore the temporal evolution of data-driven culture in organizations. Integrate external and sociocultural factors more robustly and understand the complex interplay influenced by external pressures and symbolic values.

IS researchers often adopt a functional approach grounded in the resource-based view framework to explore the concept of culture, conceiving it as an organizational resource (Anton, Oesterreich, & Teuteberg, 2021; Gupta & George, 2016; Krishnamoorthi & Mathew, 2018). In empirical research, the focus has primarily been on examining the impact of data-driven culture on business value within the contexts of big data, business analytics, and AI. Within this research, data-driven culture has been studied as a moderator between analytics capabilities and organizational performance (Agyei-Owusu et al., 2021; Behl, 2020; Campbell et al., 2021; Cao & Duan, 2014), as an antecedent for the adoption of business analytics (Duan & Cao, 2015; Medeiros & Maçada, 2022), or in relation to supply chain integration (Yu et al., 2021). However, these papers all presume a pre-existing data-driven culture defined by static characteristics such as policies (Agyei-Owusu et al., 2021) or data acquisition (Popovič et al., 2012). Our integrative framework proposes that a data-driven culture is not consistently formed by identical technical, human, or organizational characteristics but is an inherent attribute within an organization, subtly shaped by the interaction of values, tools, and individual and collective behaviors, contingent on the organizational context. Furthermore, our framework implies a reciprocal relationship, suggesting that organizational practices influence the culture just as culture influences these practices. Isolated studies support this assumption; for instance, Chatterjee et al. (2021) demonstrated that adopting techniques and tools related to business analytics could positively impact cultural forces. Similarly, Enholm et al. (2021) hypothesize that the positive relationship between culture and AI adoption is reciprocal. A significant gap exists in current research, as data-driven culture is primarily perceived as a pre-existing static organizational artifact, and it functions as an independent variable in cause-effect relationships, rather than a dependent one. Therefore, we propose the following research direction:

Research direction #1: *Future research should concentrate on empirically unraveling the dynamic interplay between organizational practices, such as the adoption of big data analytics and AI, and the evolution of a data-driven culture. This transition invites a departure from static suppositions and prompts an understanding of how assorted cultural resources and values co-evolve. Investigations of this nature would shed light on the reciprocal shaping process within the organizational context, thereby enhancing our understanding of the dual role that data-driven culture plays as both a dependent and independent variable in driving organizational performance.*

The prevailing inconsistency in the conceptualization and measurement of data-driven culture led to the proliferation of different constructs with overlapping conceptual domains. This incoherence is evident in the divergence of studies defining data-driven culture as a unidimensional entity, whereas others perceive it as a multidimensional construct. Compeau et al. (2022) posit that constructs warrant revision when empirical and theoretical assessment indicate inconsistencies or disparate theoretical conceptualizations. Our examination of empirical and theoretical research reveals irregularities and nebulous conceptualizations founded on isolated characteristics, which prove inadequate for the emergence of a data-driven culture. Our integrative framework for a data-driven culture and its resulting conceptualization serve as an initial platform for subsequent efforts towards developing suitable measures that encapsulate the complexity and dynamism of this cultural concept. Nonetheless, future studies should weigh the value of conceptualizing a data-driven culture based on a suite of individual cultural resources, against the approach of measuring unique cultural manifestations and scrutinizing their influence on particular variables. Therefore, we suggest the following research direction:

Research direction #2: *Future research should direct efforts toward conceptualizing precise measures, considering the current inconsistencies, and particularly focus on specific, measurable cultural resources within the cultural repertoire. This approach should avoid the pitfall of assuming that selected cultural resources can fully represent the intricate complexity of a data-driven culture.*

In fact, a data-driven culture constitutes a complex and dynamic concept. Measuring and defining such intricate systems pose considerable challenges (Benbya et al., 2020). Leidner and Kayworth (2006) point out that "[o]ne of the greatest challenges in IS-culture research is in defining exactly what culture is and how one goes about measuring it" (p. 380). As IS researchers grapple with complex phenomena, they increasingly gravitate towards configurational approaches, aiding in comprehending how varied configurational paths can yield the same outcome—a concept known as equifinality (Anton et al., 2022). This doctrine of causality within complex systems blends the concept of equifinality with conjunction, suggesting that an outcome is not induced by a singular condition, but rather by a configuration of conditions, and it incorporates asymmetry, indicating that the presence or absence of certain conditions or factors can yield diverse effects on the investigated outcome (Benbya et al., 2020). To better address the complexity of data-driven culture, we propose the following research direction:

Research direction #3: *Given the intricacies inherent in a data-driven culture, elucidating the underlying cause-and-effect relationships that contribute to its formation is a complex task. Equifinality, the concept that diverse initial conditions and paths can lead to the same outcome, is especially pertinent in this context. This underscores the need for a research approach that can accommodate this complexity and variability. Consequently, we recommend future studies employ more comprehensive and nuanced methods, such as qualitative comparative analysis. This approach, with its capacity to handle multifactorial relationships and recognize different paths leading to the same outcome, may provide a tool for exploring the dynamism and multifaceted nature of data-driven cultures.*

Although configurational approaches offer valuable insights, they depend on measurable or quantifiable conditions that might only capture specific facets of culture. In contrast, interpretivist approaches emphasize experiences and actions that individuals associate with culture, paying less attention to the configurational components that define culture. Interpretivist methodologies, such as ethnographies, are potentially more capable of tracing longitudinal shifts in culture, mirroring its organic emergence and changes over time as an interpretative progression (Jackson, 2011). Despite the value of interpretivism, our literature review revealed a notable scarcity of such research, even though this approach could shed light on various facets and perspectives of culture highlighted in the literature. Grover et al. (2022) suggest that the external environment and the sociocultural sphere must be more strongly integrated into culture research. Storm and Borgman (2020) demonstrated that external pressure from customers, stakeholders, and competitors could catalyze a company's

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evolution towards a data-driven culture. This may be attributed to the symbolic value and consequential strategic implications of mechanisms like stories within a data-driven culture. Such complex interconnections, driven through herd behavior or the signaling effect, are rarely captured by positivist approaches that view data-driven culture as an organizational resource.

These complexities underscore the importance of exploring more nuanced and interpretive approaches to understanding the dynamics of a data-driven culture. Consequently, we propose the following for future research:

Research direction #4: *A closer examination of data-driven culture through interpretivist methodologies (e.g., ethnographies) and different theoretical lenses is required to chronicle its temporal evolution in organizations. A more robust integration of external and sociocultural factors is essential. Additionally, a better understanding of the complex interplay influenced by external pressures and symbolic values, which is often overlooked in positivist approaches, will offer deeper insights into the essence and evolution of a data-driven culture.*

Practical Implications

To capitalize on the value-adding effects of data insights, practitioners assign highest priority to establishing a data-driven culture (Baier et al., 2022). Yet, despite these ambitions, “the difficulty of cultural change has been dramatically underestimated” (Bean & Davenport, 2019). This claim is substantiated by surveys conducted among practitioners (LaValle et al., 2011; Thomas & Randy B., 2019), indicating that few have successfully navigated the hurdles of such a cultural shift. Previous research attempted to shed light on the challenges (Berndtsson et al., 2020; Storm & Borgman, 2020) and proposes action-oriented recommendations, such as the establishment of a clear strategy and change management, alongside the provision of top management support to facilitate the desired alignment towards data-driven business (Storm & Borgman, 2020).

Similarly, practitioner reports, including those by Díaz et al. (2018), provide strategies to shape a data-driven culture, such as delineating clear goals and emphasizing CEO engagement. However, our findings reveal a prevailing issue: Many organizations struggle with the precise definition of a data-driven culture. Without a distinct understanding of the intended outcome, the efficacy and success of implemented measures can become difficult to evaluate. Our integrative framework for a data-driven culture provides insights into the individual steps that can be undertaken and how they integrate into the larger system. In reality, a combination of mechanisms is required to instill the necessary tools and values that characterize the culture.

In extending the implications of our framework, it becomes evident that the dynamics between tools and values are not static, but rather contingent upon the organizational context. Additionally, it is important to acknowledge the wider cultural sphere, as national cultures also bear influence on organizational cultures (Hofstede, 2011; Leidner & Kayworth, 2006). For instance, organizations in the Asia Pacific region, which typically uphold a more collectivist orientation, might prioritize values over tools. This focus could inadvertently downplay the toolkit perspective that spotlights individual decision-making and actions within a cultural repertoire. To address this potential imbalance, the mechanisms we delineate—stories, frames, and categories—can serve to bolster the prominence of tools, effectively countering any prevailing national biases. Moreover, it becomes increasingly critical to assess an organization's unique cultural demands and adaptations when navigating the complexities of individualism within cross-cultural teams. This is particularly true for teams that blend elements of Western and Pacific Asian cultures, each with its distinct values, communication styles, and decision-making approaches (Sinclair & Jeong, 2022).

Limitations

There are several limitations to the current research that should be considered when interpreting the results. One notable limitation is the potential for bias in the selection of literature. While efforts were made to follow established guidelines and ensure rigor in the literature selection process, it is important to acknowledge the possibility of subjectivity and its potential impact on the comprehensiveness and objectivity of the findings.

Another limitation is the geographic focus of the expert interviews, which were conducted exclusively with practitioners from Germany. This introduces a potential limitation in terms of generalizability to a broader international context. Different countries and regions may have distinct cultural, organizational, and technological factors that influence the understanding and implementation of data-driven culture. Therefore, caution should be exercised when generalizing the findings from this study to other geographical contexts. To address this limitation, future research could involve interviews with practitioners from diverse regions, allowing for a more comprehensive understanding of data-driven culture. This would not only enhance the external validity of the findings but also provide insights into potential regional differences in perspectives and practices related to data-driven culture.

Conclusion

Motivated by inconsistencies and fuzzy conceptualizations in previous research, we developed an integrative framework and defined the concept of data-driven culture to provide a more accurate understanding. This enhanced comprehension facilitates the concept's operationalization in research and supports the development of measures promoting the adoption of data-driven practices in organizations. We highlight that a data-driven culture is characterized by an organization's reliance on data to make decisions and drive business value, and is often associated to other assets such as human, technical, and organizational resources. The study also provides mechanisms that manifest values and tools in the organizational context, which contributes to a better understanding of how a data-driven culture emerges and spreads in an organization. Our framework can be used for future research to more consistently examine and measure data-driven culture.

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Appendix A

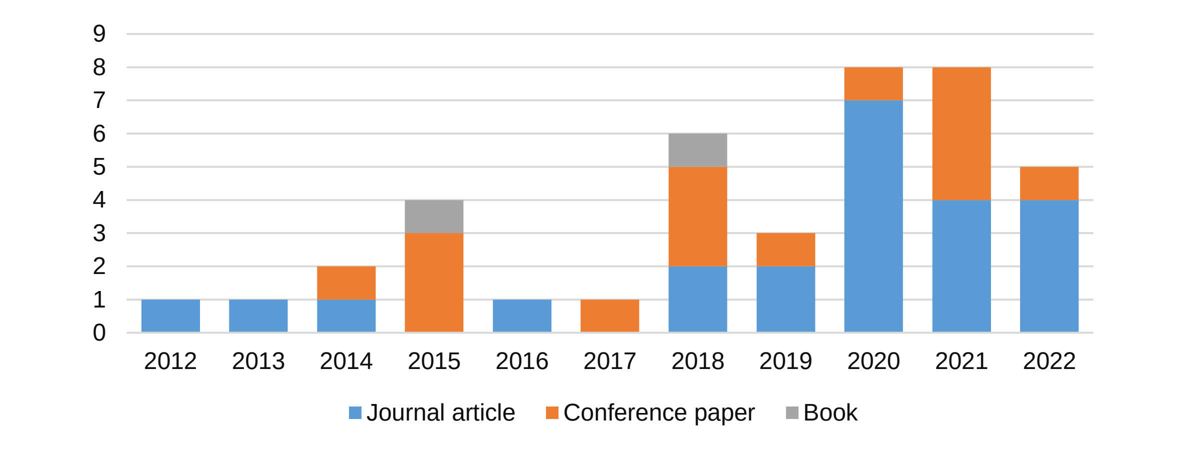

Figure A1 – Number of Studies per Year

Table A1 – Number of Studies According to Publication Type and Publication Outlet

Publication Type	Publication Outlet	Number of Studies
Journal article	Information & Management	4
	Pacific Asia Journal of the Association for Information Systems	3
	European Journal of Information Systems	2
	Decision Support Systems	2
	Management Decision	2
	International Journal of Production Economics	1
	Technology Analysis & Strategic Management	1
	Journal of Computer Information Systems	1
	European Journal of Innovation Management	1
	International Journal of Information Management	1
	European Journal of Operational Research	1
	Journal of Business Research	1
	Journal of Cleaner Production	1
	Journal of Computer Science	1
	Communications of the Association for Information Systems	1
	McKinsey Quarterly	1
	MIT Sloan Management Review	1
	Information Systems Frontiers	1
	Annals of Operations Research	1
	International Journal of Business Intelligence Research	1
	SMR-Journal of Service Management Research	1
Total number of journal articles		**29**
Conference paper	ECIS	4
	HICCS	3
	ICIS	2
	AMCIS	2
	Pre-ICIS SIGDSA Symposium	1
	PACIS	1
	Conference on e-Business, e-Services and e-Society	1
	ACIS	1
Total number of conference papers		**15**
Book		**2**
Total number of included studies		**46**

Table A2 – Literature Analysis in Regard to Data-driven Culture	
Reference	**Main findings in regard to data-driven culture**
Anton, Oesterreich, & Teuteberg (2021)	Big data analytics (BDA) management capabilities have a positive impact on operational, market, and financial performance, while BDA technical capabilities have an impact on operational performance. Both BDA technical and management capabilities, as well as business strategy and organizational factors, including a data-driven culture, are important for creating business value. More research is needed on the business value creation process of BDA and the interplay between BDA capabilities and organizational factors, and organizations should consider both technical and management capabilities in implementing BDA initiatives.
Agyei-Owusu et al. (2021)	A data-driven culture leads to increased supply chain information sharing and quality, which enhances firm performance through increased customer development.
AL-Ma'aitah (2020)	Having a data-driven culture is important for organizations to effectively handle crises, as it has a significant impact on crisis management in all stages and helps address technical challenges related to processing big data and disseminating information.
Anderson (2015)	A data-driven culture is one in which data is shared across the organization. There is a focus on setting goals and measuring success, and there is an emphasis on iteration, feedback, and learning. This culture also values data literacy and data governance, and has a top-down approach to data leadership.
Behl (2020)	Business data analytics capabilities are positively linked to customer acquisition and firm performance, and the relationship between them is moderated by organizational culture. Organizational culture plays a role in how business data analytics capabilities can help tech start-ups achieve better customer acquisition and firm performance.
Berntsson et al. (2020)	A data-driven culture is important for organizations and should include strategies for both technical and human aspects, as well as cover the entire spectrum of what it means to be data-driven. Key success factors for moving towards a data-driven organization include data literacy, leadership, governance, change management, and supporting infrastructure, while challenges include data quality, data integration, data security and privacy, and cultural resistance to change.
Campbell et al. (2021)	A data-driven culture and data quality significantly mediate the effects of analytics capabilities on organizational performance in higher education, with data-driven culture having to be established first for analytics capabilities and data quality to fully impact organizational performance. Data quality has a direct effect on organizational performance and its impact is strengthened by a data-driven culture, but a negative relationship between data quality and organizational performance suggests that data quality may be perceived as a constraint. Institutions should focus on establishing a data-driven culture and improving data quality to optimize the effects on organizational performance.
Cao & Duan (2014)	A data-driven culture mediates the effect of business analytics (BA) on information processing capabilities, which in turn mediates the effect of BA on competitive advantage. Organizations should consider implementing BA in tandem with a data-driven culture and focus on improving value, rarity, and inimitability (VRI) to maximize the benefits of BA.

Table A2 – Literature Analysis in Regard to Data-driven Culture	
Reference	**Main findings in regard to data-driven culture**
Cao & Duan (2015)	A data-driven culture mediates the effect of business analytics on strategic decision-making and organizational performance, and is important for effective business analytics use. Business analytics also improves organizational performance through its impact on information processing capabilities and resource value, rarity, and inimitability (VRI). Institutions should focus on establishing a data-driven culture and improving data quality to optimize the effects on organizational performance. A data-driven culture partially but strongly mediates the effect of business analytics on decision-making affordances, which in turn positively influence strategic decision-making and organizational performance.
Chatfield et al. (2015)	A data-driven culture is important for organizations to make data-driven decisions and generate value from big data analytics. This involves the commitment to base decisions on data and understand data as a valuable resource. It also involves overcoming departmental boundaries and power issues related to data ownership in order to foster cross-disciplinary and cross-departmental collaboration, which can be particularly challenging for established firms. Data-driven cultures are essential for organizations to take advantage of the potential benefits of big data and improve their competitiveness in the market.
Chatterjee et al. (2021)	A data-driven culture has a positive effect on the establishment of business analytics and, in combination, can improve innovation and performance. The impact of business analytics on innovation and performance is higher in firms with a strong data-driven culture. Data-driven culture is also important for improving absorptive capacity, which can improve innovation.
Díaz et al. (2018)	A data-driven culture is important for the successful adoption and use of analytics in an organization and essential for the success of data analytics initiatives. A data-driven culture should be developed by engaging the entire business and sparking employee interest and motivation. It is also important for a data-driven culture to be integrated into the overall culture of the organization, rather than being segregated. A data-driven culture can strengthen the foundation of an analytics enterprise and help avoid pitfalls, and it can be a compounding problem or solution for analytics initiatives.
Dremel (2017)	A data-driven culture is essential for successful adoption of big data analytics in the automotive industry. This culture involves executive and operational level commitment, a mindset that values data, cross-disciplinary collaboration, easy access to data pools, alignment with the overall strategy of the organization, and continuous employee education and training. Barriers to adopting big data analytics in the automotive industry include the need to develop analytical, technological, and business capabilities and domain knowledge; overcome data silos and power issues related to data ownership; and comply with security and privacy requirements.
Duan & Cao (2015)	A data-driven culture mediates the impact of business analytics on innovation in terms of new product novelty and meaningfulness. Environmental scanning also directly contributes to innovation success. The model shows low predictive power for new product meaningfulness, suggesting that other factors influence company innovation performance. An integrated approach to innovation success should be considered.
Duan et al. (2020)	Business analytics has a direct positive impact on innovation in terms of new product novelty and meaningfulness through the mediating role of a data-driven culture. Data-driven culture significantly influences business analytics and environmental scanning and has a moderating effect on the relationship between environmental scanning and new product meaningfulness.

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Table A2 – Literature Analysis in Regard to Data-driven Culture

Reference	Main findings in regard to data-driven culture
Dubey et al. (2018)	Business data analytics capabilities (BDPA) positively affect collaborative performance (CP) in supply chain collaboration programs (SCP). This relationship is moderated by organizational fit, specifically cultural orientation and resource complementarity. Temporal orientation and interdependency do not significantly affect the relationship between BDPA and CP.
Enholm et al. (2021)	Organizational culture can influence a company's decision to adopt AI as well as its ability to integrate AI into work processes. Innovative cultures are more likely to embrace AI technologies, and adaptive employees who are open to new technologies and innovations can support the deployment and use of AI in an organization. AI adoption may also lead to changes in organizational culture, including learning, collaboration, and communication patterns, and it may affect the organization's ability to innovate further.
Fischer et al. (2022)	A data-driven organization uses data and data-driven decision-making to advance operations and strategy. Further, it emphasizes the importance of having a culture that values and prioritizes the use of data. The DDO framework consists of five elements: data sourcing and sense making, data capabilities, data-driven decision-making, data-driven culture, and data-driven value creation. It has implications for both the inside-out and outside-in perspectives of an organization.
Gupta & George (2016)	A firm's business data analytics capability is positively related to its performance, and this relationship is stronger for firms with a data-driven culture. Technical and non-technical resources contribute to a firm's business data analytics capability.
Hannila et al. (2022)	A data-driven culture is essential for the success of data-driven decision-making, as well as for creating the mindset to support it. Transitioning to a data-driven approach requires creating a data-driven culture and organization and trusting data as the relevant raw material for decision-making. A company-level data model that combines master data, transaction data, and interactional data can provide a data-driven approach to decision-making and remove data silos.
Hassna & Lowry (2018)	The impact of big data capability on an organization's competitiveness and performance is moderated by the organization's market orientation and data-driven decision-making practice. Both market orientation and data-driven culture can moderate the impact of big data capability on customer sensing agility.
Holsapple et al. (2014)	Business analytics can improve an organization's performance and competitiveness when implemented successfully. Key factors for successful implementation include alignment with the organization's vision and strategy, an analytics-friendly culture, and supportive management. The Business Analytics Framework includes three dimensions and six classes of analytics perspectives and provides a foundation for understanding and communicating about business analytics.
Jesenko & Thalmann (2023)	The study highlights the necessity of a mindset shift towards a data-driven culture for sustainable implementation of data-driven service innovation (DDSI) in organizations. This shift pertains to a change in the organization’s values, attitudes, and practices that places data at the center of decision-making and innovation processes.
Kiron et al. (2013)	Analytical Innovators have a culture that values data as a core asset and supports the use of data and analytics in decision-making. This analytical mindset involves challenging the status quo, believing in the possible, and being open to new ways of thinking. In these organizations, analytics are integrated into the culture and used in strategic decisions at all levels.

Table A2 – Literature Analysis in Regard to Data-driven Culture	
Reference	**Main findings in regard to data-driven culture**
Kloeckner et al. (2018)	A data-driven culture is important for organizations to improve the effectiveness of automation and drive a culture of continuous improvement. Adopting a data-driven approach can improve mean time to recovery by up to 90%. Establishing a data science competency and hiring a Chief Data Officer can also support the adoption of data-driven approaches.
Medeiros & Maçada (2022)	Successful use of business analytics in customer acquisition is supported by a data-driven culture and behavior that fosters the use of business data and analytics resources. Business analytics directly affects customer acquisition and is transmitted through organizational agility. Data-driven culture also plays a role in the acquisition of customers.
Mikalef et al. (2018)	A firm's big data analytics capability has a positive impact on its innovative capability, which is strengthened by information governance and a data-driven culture.
Mikalef et al. (2019)	This study emphasizes that not all organizations operate under the same conditions and, therefore, require a tailored approach to investing and deploying their big data analytics resources. The study suggests that a combination of technological, organizational, and managerial resources From a practical perspective, the study recommends recruiting individuals with technical and managerial understanding, fostering organizational learning, and integrating big data decision-making. It advises managers to benchmark strengths and weaknesses, develop a data-driven culture, and consider the time and complexity of resource development.
Mikalef & Krogstie (2020)	The study's findings highlight the influence of big data analytics (BDA) on both incremental and radical process innovation capabilities. The research underscores the pivotal role of data resources and managerial skills in attaining high levels of innovation. Service-based firms benefit greatly from a data-driven culture for radical process innovation, whereas product-based firms place more emphasis on managerial competence. Technical skills are crucial for incremental process innovation. Additionally, contextual factors like industry type and organizational size shape the required resources and approaches. By considering these insights, managers can develop effective strategies based on their specific BDA initiatives and desired process innovation goals.
Mikalef, Pappas et al. (2020)	A firm's big data analytics capability can improve its dynamic capabilities, which strengthen its marketing and technological capabilities. A data-driven culture can enhance the relationship between a firm's big data analytics capability and its operational capabilities. Dynamic capabilities mediate the relationship between big data analytics capability and marketing capabilities, but not between big data analytics capability and technological capabilities.
Oesterreich et al. (2021)	The adoption of augmented analytics is positively influenced by establishing a data-driven culture. Future research should focus on transparency and explainable AI, data governance, and the design and implementation of AI-driven analytics systems in organizations.
Oesterreich, Anton, & Teuteberg (2022)	A data-driven organizational culture is necessary for the effective use of business analytics and data-driven decision-making, while the success of business analytics depends on various factors such as personnel resources and management capabilities.

Table A2 – Literature Analysis in Regard to Data-driven Culture	
Reference	**Main findings in regard to data-driven culture**
Pai & Chandra (2022)	The study uses the Technology-Organization-Environment (TOE) and Carroll's CSR frameworks to examine factors influencing the adoption of AI in CSR activities among Indian firms. It provides insights into nine key factors that drive AI adoption in CSR, noting variations based on the size, public or private orientation, and industry sector of the firm. These findings are significant to firms, AI product companies, strategists, and developers, emphasizing the need for integrating CSR, which is a triple bottom line approach, into a company's culture, decision-making, and operations for societal benefit.
Pethig (2018)	A data-driven culture is important for organizations to establish in order to make data-driven decisions and generate value from big data analytics. This involves a commitment to using data to inform decision-making on both the executive and operational level, as well as a mindset that views data as a valuable resource. Adopting a data-driven culture can be challenging and involve resitance to change, particularly in established organizations. Data-driven cultures are essential for organizations to take advantage of the potential benefits of big data and improve their competitiveness in the market.
Popovič et al. (2012)	A data-driven culture is important for organizations to make data-driven decisions, generate value from big data analytics, and improve their competitiveness in the market. It involves a commitment to using data to inform decision-making on both the executive and operational level, as well as a mindset that views data as a valuable resource. It also involves overcoming departmental boundaries and power issues related to data ownership in order to foster cross-disciplinary and cross-departmental collaboration. Adopting a data-driven culture can be challenging and involve resitance to change, particularly in established organizations. Adopting a data-driven culture is essential for organizations to take advantage of the potential benefits of big data and improve their competitiveness in the market.
Ramakrishnan et al. (2020)	A data-driven culture is important for the effectiveness of business intelligence and analytics (BI&A). In addition, BI&A innovation infrastructure capability, customer process capability, and B2B process capability are important factors in improving organizational performance through the use of BI&A. The integration capability of BI&A may negatively impact its effectiveness, possibly due to early implementation stages in the study sample.
Radhakrishnan et al. (2022)	From a cultural perspective, the paper highlights the significance of AI in supporting business strategies and social impact measures. It also underscores the influence of top management support, organizational culture and readiness, social influence, and mimetic and normative pressure in digital work adoption. Organizational factors including agility, financial readiness, alignment of politics, culture, priorities, and AI training programs facilitate AI adoption, while barriers such as lack of capability, resistance to change, and fear of failure impede it.
Shamim et al. (2019)	A data-driven culture is essential for the successful development of big data decision-making capabilities. Factors such as leadership, talent management, and technology also play a role in the development of these capabilities. Managers can assess their data management practices and create value from data by considering these factors.

Table A2 – Literature Analysis in Regard to Data-driven Culture

Reference	Main findings in regard to data-driven culture
Shan et al. (2019)	An open culture, characterized by information sharing and communication between IT and business groups, is important for the successful adoption of big data analytics (BDA). This open culture can help reduce risks and make it easier for companies to adapt to technological and market changes. In addition, an open culture is conducive to using BDA as a tool for evidence-based decision-making. Resources, including IT technology resources, IT relationship resources, and idle resources, as well as dynamic capabilities, such as IT technology capabilities, compatibility, and strategy flexibility play a role in the competitiveness of an organization through the adoption of BDA.
Shao et al. (2022)	The study found that data-driven culture, data analytics affordance, and individual absorptive capacity have significant effects on employees' data analytics skills, with absorptive capacity having the strongest influence. Data analytics skills were found to have strong influences on both task performance and innovative performance, while data-driven culture and data analytics affordance have different levels of influence on digital natives and digital immigrants.
Storm & Borgman (2020)	A data-driven culture is created through top-management, communication, change agents, and external pressure. It is considered achieved when it is evident at all corporate levels and implemented in day-to-day operations. Challenges in creating a data-driven culture include resistance to new technology, a lack of focus on providing usable analysis, and a lack of data literacy among employees. Leadership becomes more important at higher levels of data-driven culture maturity.
Upadhyay & Kumar (2020)	Big data capabilities and an inclusive and conducive organizational culture are important for improving organizational performance by transforming tacit into explicit knowledge in business operations. Organizational culture plays a role in leveraging big data capabilities and internal knowledge. This study combines the effects of the organizational culture and big data capabilities in an integrated model.
Visvizi et al. (2022)	A data-driven culture values learning, data, and innovation and is supported by technological infrastructure and the sharing and enhancement of resources and skills. Adopting a data-driven approach can lead to improved decision-making and the development of new products and services, as well as increased sustainability and well-being for stakeholders.
Windt et al. (2019)	A data-driven culture is essential for the successful transformation of an organization towards a data-driven approach. Leadership plays a key role in communicating the value of data-driven decision-making, securing and managing resources, and creating a data-driven culture. However, these efforts can be challenged by the need to secure and manage resources such as data, analysts, and budgets.
Yu et al. (2021)	A data-driven culture can facilitate supply chain finance integration and improve organizational performance by enhancing the effect of big data analytics on information processing capacity. Big data analytics capabilities also have a positive effect on supply chain finance integration through the mediation of the data-driven culture. It is important to establish internal supply chain finance integration before implementing integration with customers and suppliers.
Yu et al. (2022)	This study reveals that the adoption of Big Data Analytics (BDA) in managerial decision-making is influenced by factors such as technology readiness, data quality, managerial and organizational knowledge of BDA, and organizational expectations. It was found that a clearly emphasized organizational expectation, derived from a data-driven culture, significantly drives BDA adoption by aligning employee actions with company goals.

Appendix B

Table B1 – Pool of Characteristics of a Data-driven Culture

Characteristic	Description
Principle that decisions in a company are reached on the basis of data	Adopting a data-driven approach to decision-making, where decisions are based on evidence and data.
Fact-based decision-making occurs at all levels of the hierarchy	Data-driven decision-making should be prevalent at all levels of the organization, from top management to front-line employees.
Using data to optimize operations and business processes	Using data to optimize operations and business processes can help improve efficiency and effectiveness.
Using data insights to advance innovation	Using data helps an organization to drive innovation and develop new or improved products and services.
Awareness of the importance of data and evidence-based problem solving should prevail within the entire organization	It is important for all employees to understand the value of data and the importance of using it to inform decision-making.
Norms, values, and behaviors in which evidence-based problem solving (and recognition) is of high priority	A data-driven culture should prioritize the use of evidence and data to solve problems and make decisions.
Policies for data governance	Establishing clear policies for data governance helps ensure the responsible and ethical use of data within the organization.
Digitized processes to drive data collection within the organization	Implementing digital processes for data collection can improve efficiency and accuracy and supports a data-driven culture.
Trained workforce in data management and the use of analytics tools	Ensuring that employees have the necessary skills and knowledge to effectively manage and analyze data is crucial for a data-driven culture. This can involve providing training and education on data management and analytics tools.
Appropriate recruitment or educational efforts to create awareness and understanding among an organization's workforce about the value of data as an asset and its impact on the business	Providing education and training to employees on the value and importance of data can help create a data-driven culture.
A systematic approach to create, collect, and consolidate data	Having a structured and organized approach to creating, collecting, and consolidating data helps ensure the quality and reliability of the data being used for decision-making.
Use of advanced analytics technologies and tools for data operations and processing	Utilizing advanced analytics technologies and tools can help an organization extract insights and value from its data.
Organization that provides every employee the opportunity to access data independently	Ensuring that all employees have access to data enables them to make data-driven decisions and contribute to a culture of using data to inform decision-making.
Availability of and access to data	Having access to the data needed for decision-making is essential for a data-driven culture.
Ensuring the consistency, completeness, correctness, and integrity of data	Ensuring the quality and reliability of the data being used is essential for a data-driven culture.
Definition and regular use of KPIs for business management	Using key performance indicators (KPIs) to measure and track progress can help support a data-driven culture.
An environment of constant experimentation and learning	Fostering a culture of experimentation and learning, where employees are eager to test new ideas and approaches, can support a data-driven culture.
Willingness on the part of employees to learn and experiment	A data-driven culture requires employees willing to learn and try.

About the Authors

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