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Building Data-Driven Organizations: A Theoretical Exploration of the Role of leadership in Big Data Management

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ABSTRACT

Problem: The adoption of Big Data and business intelligence is often limited by the lack of leadership with the necessary skills to manage the information provided by the data. This is compounded by the absence of an organization with an established data-driven culture.

Objective: The objective of this study is to analyze how the role of leadership influences the development of a data-driven organizational culture and how this relates to Big Data management.

Methodology: A mixed-methods approach was used, based on a systematic literature review of high-impact databases such as Scopus and Web of Science regarding leadership, organizational culture, Big Data, data culture, and decision-making processes published between 2015 and 2025.

Results: The study identified four key drivers: data analysis, data democratization, data-driven leadership, and ethics in data-driven decision-making.

Conclusions: The study confirms that data analytics, information democratization, data-driven leadership, and a data culture are essential pillars for moving toward truly evidence-based organizations. The coherent integration of these four drivers enables organizations to address the challenges arising from informational complexity and fosters more responsible, ethical, and strategic decision-making. However, it is acknowledged that consolidating this approach requires leadership capable of guiding cultural transformation and mitigating the risks associated with data overload, which defines the scope of this study and opens opportunities for future research..

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1. Introduction

In the digital age, companies face the challenge of possessing unprecedented volumes of data. However, despite having these data, they do not always manage to transform them into competitive advantages. Authors such as Gasimova (2016), Sivarajah et al. (2017), Riahi et al. (2018), and Uddin Murad et al. (2022) and the basic characteristics and features of big data.","container-title":"Problems of Information Technology","DOI":"10.25045/jpit.v07.i1.09","ISSN":"20774001, 23040157","issue":"1","journalAbbreviation":"JPIT","language":"en","page":"62-78","source":"DOI.org (Crossrefindicate that Big Data are distinguished by their volume, velocity, and variety, which, in terms of capture, storage, processing, and analysis, can sometimes make them difficult to manage. Accumulating data does not guarantee value; what is essential is the ability to extract strategic knowledge.

Studies such as those of Bowers et al. (2017) and Chatterjee et al. (2024)often with disastrous results. When the crisis gets out of hand, these organizations realize belatedly that the current leader does not necessarily possess the leadership style required to manage the crisis effectively. We present three crisis response leadership principles (CRLP emphasize that successful and lagging organizations differ in their analytical culture. Successful organizations have the ability to transform data into processed information, their findings into knowledge, and this knowledge into strategic decisions. This requires both technology and leadership with analytical skills.

Similarly, Carillo (2017) and Agrawal et al. (2023) "container-title":"The TQM Journal","DOI":"10.1108/TQM-12-2020-0285","ISSN":"1754-2731","issue":"1","journalAbbreviation":"TQM","language":"en","page":"73-101","source":"DOI.org (Crossrefshow that companies that achieve better results both financially and in terms of innovation are those that adopt a *data-driven approach* versus those that base their decisions on intuition or experience.

It is possible to distinguish studies that focus on analyzing how leaders who possess analytical skills generate agile, innovative, and learning-oriented organizations (Başak et al., 2022). The ability to understand Big Data processes directly impacts the quality of business intelligence, as this allows data to be transformed into reliable information (Connely et al., 2000), which can serve as a bridge between the leader's vision, technological complexity, and business action, thus contributing to the organization's real value.

An undeniable challenge is not the lack of data but rather the ability to align technology with human talent and leadership styles and thereby turn data into strategic assets that can drive innovation and competitiveness in a sustained manner (Uddin Murad et al., 2022).

Despite the increasingly well-recognized benefits of data-driven leadership (Abdullahi et al., 2020), the literature still lacks research on how to effectively integrate traditional leadership styles with a data-driven approach, as well as how to build data-driven organizations.

Therefore, it is necessary to train leaders with analytical skills and strategic vision to ensure the proper management of Big Data and enhance the effectiveness of business intelligence, thus making it possible to consolidate sustainable competitive advantages in the digital age.

This article aims to explain how leadership styles influence the ability of organizations to manage Big Data and optimize effectiveness, and their impact on building a data-oriented organizational culture.

In addressing these objectives, this paper aims to contribute more deeply to how data-driven leadership enables better information management and optimal business results, as a data-driven culture prioritizes informed decision-making that leads to more accurate strategies.

This article is organized into five sections that coherently articulate the study's purpose. First, the theoretical framework is presented, including the concepts of data-driven leadership, data-driven culture, and Big Data models, highlighting the links and tensions between them as identified in recent literature. The second section details the methodological design, which combines bibliometric analysis with a systematic review to examine the evolution, patterns, and gaps in this field. The third section presents the quantitative and qualitative results derived from the scientific mapping and thematic analysis. Subsequently, the discussion links these findings to contemporary theoretical debates, including the alignment between the most widely cited leadership styles and the four identified drivers: data analytics, data democratization, data-driven and knowledge-based leadership, and building a culture oriented toward the strategic use of data. Finally, the conclusions, theoretical and practical implications, limitations, and future research directions that emerge from this study are presented.

2. Theoretical Foundation

2.1. Data-Driven Leadership

Data-driven leadership, as a concept, arises at the intersection of research on evidence-based decision-making, organizational leadership, and information management (Bratasanu, 2018). In recent years, as organizations have improved their ability to capture and process large volumes of information, the literature has focused on the availability of data for managerial needs, thereby enabling input into governance, decision-making, and organizational change processes (Brynjolfsson et al., 2011; Canning & Found, 2015). This has meant that leadership is no longer viewed or defined solely according to traditional styles, but rather by the ability to translate analytical elements into operational and cultural strategies that promote the responsible and effective adoption of data at all levels of an organization (Mikalef et al., 2020; Hashim et al., 2025).

Furthermore, data-driven leadership can be understood as the set of managerial capabilities that combine: (a) the cognitive–strategic (Connely et al., 2000), which relates to the ability to understand and use evidence for strategy development; (b) the relational–cultural (Chatterjee et al., 2024), that is, the ability to mobilize and align teams, as well as to promote data literacy and build trust in the use of information; and (c) the technological–institutional (Fothergill et al., 2019), which implies the competencies required to promote architectures and governance that ensure the quality, accessibility, and ethical use of data. In short, data-driven leadership acts as a facilitator of digital capabilities (Wamba et al., 2017) that generate value for an organization when they are successfully integrated with appropriate routines and structures.

An important theme in recent literature is the increasing dominance of managerial models in the transition from intuition-driven to analytics-based decision-making (Brynjolfsson et al., 2011; Fawcett & Provost, 2013; Korherr et al., 2022; Chidera et al., 2024; Ghafoori et al., 2024). This can be linked to emerging capabilities or competencies that include analytical literacy, enabling the integration of metrics and models, as well as narrative skills for communicating findings (Vidgen et al., 2017) and the ability to align technology with strategy. López-Figueroa et al. (2025) indicate that having a data-savvy leader is not sufficient to achieve organizational transformation; complementary roles such as analytics are also required, as well as data translators and stewards distributed throughout the organizational structure (Korherr et al., 2022).

Leaders face significant challenges, including cultural resistance and potential distrust of algorithmic models. There may also be skill gaps in middle management, as well as information overload and ethical tensions. To mitigate these risks, leadership must act as a driver of adoption, integrating governance frameworks with clear accountability.

2.2. Data Culture

Data culture can refer to shared patterns of beliefs, values, and organizational norms that legitimize the use of data as an input for decision-making and collective action. Recent literature (Vidgen et al., 2017; Wamba et al., 2017; Dubey et al., 2019) has shown that, more than a technology-centric approach, culture is the primary factor when justifying investments in analytics and ensuring that these contribute to tangible results; without a data culture, tools tend to remain underutilized or fragmented. Data culture includes cognitive components such as the value of evidence, as well as procedural and structural components such as governance.

Some studies (Mikalef & Krogstie, 2019; Ghafoori et al., 2024; Hashim et al., 2025) have proposed operational dimensions to diagnose and promote culture, including: (a) attitudes and capabilities, (b) literacy, (c) governance, and (d) infrastructure. Such integration enables the evaluation and measurement of the maturity of a data-based culture and thereby the design of interventions in this direction.

Democratization of data is a central objective when establishing a data-driven culture, but this requires governance. According to studies such as those by Huynh et al. (2023), Oliver et al. (2023), and Salerno & Maçada (2025), democratization without governance can lead to unfavorable decisions and conflicts with the authority of information. Governance implies, among other things, quality assurance processes and the inclusion of access policies. A mature data culture relies on the incorporation of ethical practices and explainability protocols.

A data culture will institutionalize ethical norms including, for example, reviews of consent processes and auditing mechanisms. The legitimacy of data use depends on visible ethical practices; otherwise, trust and the sustainability of such a culture would be eroded (Massaroni, Enrico et al., 2018; Kumar, 2025).

Such adoption of a data culture often fails when middle management lack the skills to interpret and apply the results; therefore, an effective strategy that combines both democratization and training is required; data literacy is mandatory, and relevant operational support is required (Mikalef et al., 2020; Korherr et al., 2022).

Anotehr aspect to consider is information overload, which materializes as a real risk; indeed, the proliferation of metrics and dashboards without prioritization criteria can lead to decision-making paralysis (Peng et al., 2011; Bratasanu, 2018; Dubey et al., 2019). In this regard, from a cultural perspective, an appropriate response would be to consolidate routines for filtering, prioritizing indicators, and developing analytical processes.

2.3. Big Data Models

The adoption of Big Data in organizational environments is not merely a technological phenomenon, but rather involves strategic and managerial elements. In this sense, Big Data can be approached as a comprehensive framework describing how organizations can capture, process, analyze, and use data to create value (Gupta & George, 2016; Mikalef & Krogstie, 2019; Ghafoori et al., 2024), and not just algorithms or architectures.

A Big Data model in the organizational environment addresses two dimensions simultaneously: on the one hand, organizational capabilities and management processes, and on the other, technological support and data governance. The literature (Mikalef & Krogstie, 2019; Mikalef et al., 2020; Wamba et al., 2017; Uddin Murad et al., 2022; Ngo et al., 2020) argues that value creation is achieved when both dimensions are aligned with a company's objectives, culture, and management capabilities.

Furthermore, the literature offers several approaches to Big Data, such as viewing analytical capabilities as a competitive advantage. Along these lines, Gupta & George (2016), Wamba et al. (2017), Mikalef & Krogstie (2019), and Mikalef et al. (2020) include the perspectives of resource-based views and dynamic capabilities to propose models that define critical components. While such models address important criteria such as technological resources, human resources, organizational processes, and the relationship with strategy, the authors argue that simply having the technology is not sufficient; these critical elements must be combined to generate sustainable value from Big Data.

Big Data architectures have a significant technical architectural component, and management literature highlights the impact of this on decision-making. The focus is not on choosing a pattern, but on implementing structures that enable consistent, reliable, and trackable decision-making (Demirezen & Navruz, 2023).

In this vein, governance has become an essential component of Big Data organizational models. Governance encompasses not only technical controls but also institutional coordination structures, accountability, and evaluation and monitoring. It enables shared responsibility for the results of analyses, especially when reporting on sensitive decisions (Baesens et al., 2016; Chatterjee et al., 2024).

Despite conceptual progress, models continue to face latent challenges, such as a lack of talent including analytical skills and analytical translation capabilities, an excess of unprioritized information, organizational silos, and resistance to change. Managing organizational change is just as important as investing in technology. Leadership must play an active role in aligning expectations, structures, and metrics (Oliver et al., 2023; Hashim et al., 2025; Kumar, 2025; Salerno & Maçada, 2025).

3. Methodology

This study adopts a mixed-methods approach, combining a systematic literature review with bibliometric analysis. This combination of a systematic literature review with bibliometric analysis has become a robust methodology in the field of management and organizational studies. Recent research has proven useful for mapping trends, identifying conceptual gaps, and structuring emerging domains related to digital transformation, data-driven culture, and, of course, organizational leadership. These approaches involve a comprehensive methodology (including search activities, inclusion criteria, data extraction, and synthesis) to map the scientific output on the role of leadership in building data-driven organizations. This enables the identification of trends, authors, and predominant thematic areas. Similarly, in areas related to this study, similar approaches have been applied to examine the capabilities of Big Data (Huynh et al., 2023), organizational culture (Kumar, 2025), and leadership in digital contexts (Sağbaş & Erdoğan, 2022), clarifying complex and multidimensional constructs such as the drivers of data-driven culture (Oliver et al., 2023; Salerno & Maçada, 2025). This enables the combination, organization, and understanding of the evolution of knowledge regarding leadership styles and their role in building an organizational culture oriented toward the strategic use of data.

The search strategy adopted to achieve this included three phases: (1) study identification, (2) study selection, and (3) an analysis to identify key elements. This strategy is presented in **Fig. 1**, including the inclusion and exclusion criteria for the articles.

3.1. Stage 1: Case Selection

Scopus and Web of Science (WoS) were chosen because both offer superior performance compared with other search engines. The document type was defined as articles published between 2015 and 2025. The keywords used in the initial search were “data culture”, “data capability”, “big data”, and “data analysis”. Using these criteria, the Scopus search returned 267 articles.

Meanwhile, in WoS, search strings were applied to titles, keywords, and abstracts of publications to increase the possibility of obtaining an overview of the discourses on the considered concepts and their applications.

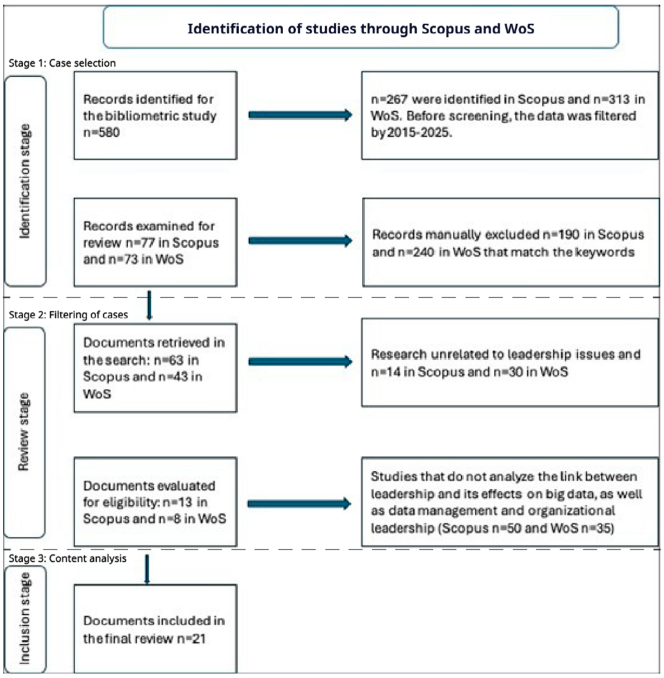
The type of documents selected was articles for both databases. The results reveal that this topic cuts across research disciplines, including perspectives from economics, administration, management sciences, construction, and education, among others; these are the fields where it is currently attracing most interest.

To achieve a wider reach for the contributions, the search string used was as follows:

(TITLE) (Data culture) OR TITLE (data - driven) OR TITLE (big Data and Title (leadership))) AND PUBYEAR > 201 5 AND PUBYEAR < 202 5 AND (LIMIT -TO (DOCTYPE , “ar “)) AND (LIMIT -TO (LANGUAGE , “English “)

Allso, Fig. 1 illustrates the procedures used in each of the stages, as well as the number of items considered.

Fig. 1. *PRISMA flowchart by levels.*



In this stage, the articles were screened to eliminate irrelevant or duplicate items. At the end of this process, a total of ten articles met the established criteria.

3.3. Stage 2: Selection of Studies

Practical criteria recognizing the rapid evolution of studies on Big Data and the skills required for decision-making and the need for a data-driven culture were established to guarantee the quality of the included studies.

Irrelevant and duplicate articles were eliminated. Publication sources were limited to journals written in English language. The following criteria were then established: (1) the article had to focus on the concept of Big Data, primarily its application to the topic of skills for its management; (2) the article also had to include, in its discussion, the topic of data-driven organizational culture; (3) the article had to address the incorporation of ethical elements into data-driven activities.

Table 1 presents the combination of stages 1 and 2 with respect to the keywords used in the search string and the number of articles remaining in each phase.

Table 1. *Inclusion criteria for articles.*

Stage 1		
Keywords	**Search element**	**Number of items**
"data culture", "data-driven", "big data", "data analytics", "leadership", "decision-making"	Qualification	230
"Data culture"	Qualification	
"data culture", "data-driven", "big data", "data analytics", "leadership", "decision-making"	Title, abstract, keywords	126
Selection criteria	Articles in English language Removal of duplicates Published between 2015 and 2025	48
Stage 2		
Inclusion criteria	**Exclusion criteria**	**Number of items**
The article should focus on the concept of Big Data, mainly its application to the topic of skills for management	Articles that did not present a representative argument about Big Data and the skills needed to manage them	230
The article should also reflect in its discussion the topic of data-driven organizational culture	Concepts such as data-driven culture or skills are rarely mentioned in the article	126
The article aimed to focus on incorporating ethical elements into data-based activities	The ethical component is not adequately addressed in the discussion of the article	48

3.3. Stage 3: Content Analysis

In this third stage, qualitative content analysis and synthesis of the selected literature was carried out to identify the impact of leaders' skills in data-driven decision-making as well as the construction of a data culture in the organization. Krippendorff (2013) indicates that it is necessary to address the specific context of the writing of the article, and also describes that the content analysis must be both exclusive and exhaustive.

The categories in this study were developed inductively. These categories emerged from the contextualization process, that is, from the identification of relevant elements in the articles' content, which allowed for content analysis based on: (1) profiling the included articles according to their context and their relevant contribution to data culture; (2) categorization of the components based on their characteristics; and (3) a comparison of the arguments among the authors.

4. Results and Analysis

This section presents the research findings, including the bibliometric analysis and a descriptive analysis of the identified articles, as well as a categorization of data-driven culture. On this basis, the key elements that drive the construction of a data-driven culture are detailed; these can be classified into four conceptual elements and four key drivers, in addition to organizational factors considered to be essential for the establishment of such a culture.

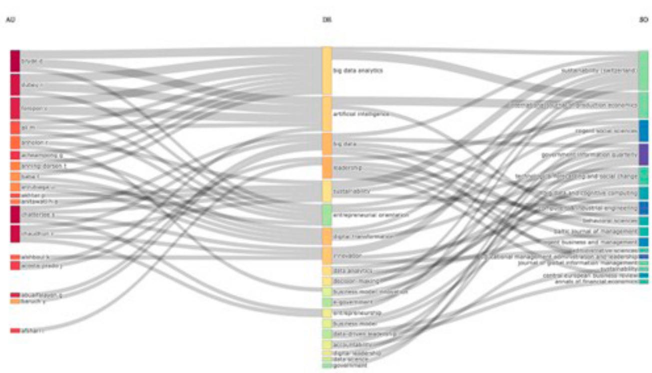
Table 2. *Main information about the field.*

Characteristic	**Result**
Timespan	2015–2025
Source articles	48
Annual growth rate (%)	23.11
Average age (years)	2.37
Average citations per document	32.77
Document contents	
Keywords plus	279
Author's keywords	261
Authors	
Authors	227
Authors of single-author documents	7
Author collaboration	
Single-author documents	7
Co-authors per document	3.87
International co-autohrships (%)	8.33

4.1. Scientific Production

The bibliometric analysis identified relevant patterns in the scientific production in this study area focusing on Big Data, data analytics, leadership, and data-driven approaches. The database included a total of 48 articles, revealing relationships between authors, keywords, and scientific journals.

Fig. 2. *Three-field plot.*



Gasimova (2016), Akhtar et al., (2019), Sivarajah et al. (2017), and Verma & Bhattacharyya (2017) 2017focus on applied research in the use of data analytics for the optimization of production processes. This confirms that researchers usually consider specific thematic areas, leading to the construction of lines of research (Mikalef & Krogstie, 2019) the objective of this paper is to survey the status quo of technical and businessrelated data analytics skills in a range of different industries and identify the most important skills that will be needed in the next few years. To do so, this study builds on a sample of 202 survey responses from key executives from Norwegian firms. Our analysis reveals the level of skill-fulfilment in for technically and business-oriented employees in a number of key industries. In addition, we use survey data from an additional sample of 27 executives and interviews with 6 managers and provide a ranking of the perceived importance of data analytics-related skills according to respondents in three categories, technical skills, business and project management skills, and soft skills. Our study concludes with findings regarding the skill-gap that exists in the domain of data science as well as suggestions on how to fulfil these needs, indicating specific subject-areas that are of heightened importance.","container-title":"2019 IEEE Global Engineering Education Conference (EDUCON.

Analyzing collaborations among authors, it was observed that researchers with a larger number of publications also have a greater number of co-authorships, suggesting that this field of knowledge is typically collaborative and tends to focus on significant academic networks. According to Kumari (2019), scientific collaboration facilitates the consolidation of knowledge and the emergence of new thematic areas.

4.2. Keyword and Trend Analysis

The review of keywords allowed us to identify the most recurrent terms, with the most predominant being, for example, Big Data analysis, data-driven, decision-making, and organizational culture (Fig. 3). These terms reflect not only a consolidation of traditional topics but also emerging themes related to organizational transformation through the establishment of a data-driven culture.

Cluster generation based on co-occurrence analysis (Fig. 4) and frequency showed that some terms, such as "Big Data analysis", form a central cluster, reflecting the tendency of authors to include these themes in their publications. Furthermore, the terms "leadership" and "data analysis" form secondary clusters, which could reflect a growing thematic diversification in recent literature.

Fig. 3. *Thematic map.*

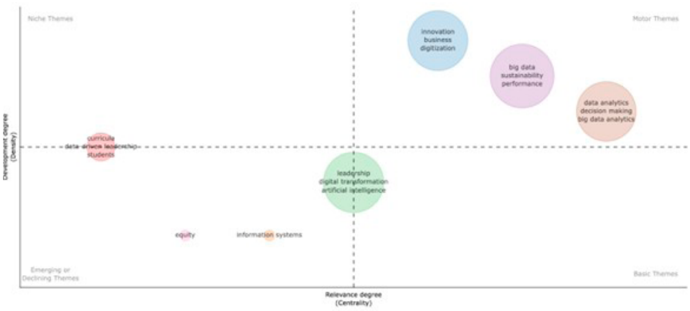


Fig. 4. *Co-occurrence network.*

The temporal analysis revealed a significant increase in publications since 2020, coinciding with the acceleration of digital transformation in the business field.

The influence of leadership on the adoption of technologies and data-driven management (Alaimo & Kallinikos, 2022; Barros-Contreras et al., 2022; Cheong, 2016) digital technologies transform the process of knowing and the knowledge functions data fulfil in socioeconomic life. These functions are most of the times mediated by putting together disperse and steadily updatable data in more stable entities we refer to as data objects. Users, customers, products, physical machines rendered as data objects become the technical and cognitive means through which organizational knowledge, patterns and practices develop. Such conditions loosen the dependence of data from domain knowledge, reorder the relative significance of internal versus external references in organizations, and contribute to a paradigmatic contemporary development that we identify with the decentering of organizations of which digital platforms are an important specimen.","container-title":"Organization Science","DOI":"10.1287/orsc.2021.1552", "ISSN":"1047-7039, 1526-5455","issue":"1","journalAbbreviation":"Organization Science","language":"en","page":"19-37","source":"DOI.org (Crossrefis anotehr relevant dimension that emerges from this analysis. Organizations and authors who promote data-driven management tend to publish research that emphasizes the need for proactive, strategic leadership focused on knowledge sharing at all levels of an organization.

Thus, the framework for a data-driven culture, the decision-making process, and ethical considerations in data-driven decision-making are based on the following interrelationships:

4.3. The Culture of Production

This element consists of institutionalized routines, as well as habits and knowledge practices, within an organization (Agrawal et al., 2023; Akhtar et al., 2019; Hashim et al., 2025)"container-title":"The TQM Journal","DOI":"10.1108/TQM-12-2020-0285","ISSN":"1754-2731","issue":"1","journalAbbreviation":"TQM","language":"en","page":"73-101","source":"DOI.org (Crossref. To achieve proper development and ensure that this culture becomes established and is maintained, a sense of leadership is required to stimuate continuous generation of knowledge and its sharing among teams at all levels of the organization. Knowledge management is a function that promotes such knowledge-sharing practices (Ahmad, 2015; Alavi & Denford, 2011; Al-Busaidi & Olfman, 2017; Connely et al., 2000; Layden et al., 2024)this study attempts to develop a model for successful BI deployment and empirically examines the association between BI deployment and sustainable competitive advantage. Taking the telecommunications industry in Malaysia as a case example, the research particularly focuses on the influencing perceptions held by telecommunications decision makers and executives on factors that impact successful BI deployment. The research further investigates the relationship between successful BI deployment and sustainable competitive advantage of the telecommunications organizations. Another important aim of this study is to determine the effect of moderating factors such as organization culture, business strategy, and use of BI tools on BI deployment and the sustainability of firm's competitive advantage. This research uses combination of resource-based theory and diffusion of innovation (DOI and can assist the performance of data-driven leadership, which is also related to this production culture.

4.4. Data Integration

Data can flow through the data–information–knowledge–wisdom (DIKW) hierarchy, which exhibits relative flexibility to incorporate different types of information. Data integration and data cultivation enable decision-makers to answer questions that are not usually addressed in more traditional modeling and simulation processes. This process can be compared to the collection and organization of data analytics, allowing for the discovery of useful information.

Data can be cultivated in various ways, and also cross-pollinated and distributed by other agents, such as users, government, and other corporations. Incorporating a data farming strategy democratizes access to knowledge within the organization, reduces reliance on intuition, and strengthens interdisciplinary collaboration. This not only generates data but also fosters behaviors geared toward experimentation, validation, and the responsible use of information, which is fundamental for a sustainable and transformative data-driven culture.

4.5. Datafication

This is a complex process that can enhance the meaning of data to influence behaviors, values, and subjective elements. With the growing availability, volume, and variability of data, effective analysis is considered to become a key differentiator in marketing (Lycett, 2013). In reality, data are often messy, come from multiple sources, and are present in various formats. Understanding which data can be discarded, their availability, the degree of data loss during cleaning, their semantic integration, and the versatility of their representation creates an important link with decision-making and action execution.

In this regard, one should reflect on what is required to generate business value. The way in which products and services are delivered and consumed may be increasingly automated, but this is insufficient to generate value. Datafication is one perspective within this reflection, focusing on the characteristics of companies that depend on data and data infrastructures, as well as transforming those data into something valuable.

The potential of this lies in improving the organization's efficiency and revenue (Nwachukwu & Hieu, 2021)2021. This also requires governance structures, digital literacy, and ethical criteria that guarantee the responsible use of information.

For such a datafication process to be effective, active facilitation of data management is necessary. This contributes to improved data management, which in turn improves the status quo in industries (Brynjolfsson et al., 2011)we find that firms that adopt DDD have output and productivity that is 56% higher than what would be expected given their other investments and information technology usage. Furthermore, the relationship between DDD and performance also appears in other performance measures such as asset utilization, return on equity and market value. Using instrumental variables methods, we find evidence that the effect of DDD on the productivity do not appear to be due to reverse causality. Our results provide some of the first large scale data on the direct connection between data-driven decision making and firm performance.","container-title":"SSRN Electronic Journal","DOI":"10.2139/ssrn.1819486","ISSN":"1556-5068","journalAbbreviation":"SSRN Journal","language":"en","source":"DOI.org (Crossref. This process fosters an empirical view of management, where perceptions and intuition complement, and in some cases are superseded by, evidence. At the same time, validation requires analytical skills and digital competencies that promote cultural transformation, leading to the adoption of collaborative practices based on measurable results.

Datafication is more than a technological revolution; it represents a cultural and cognitive transformation that redefines how organizations learn and make decisions while building knowledge.

4.6. Data Infrastructure

This element makes it possible to encourage data consumption and sharing. At the same time, it lays the foundation for the organization to create, use, and secure data. Those who invest in data infrastructure necessarily require data literacy to be successful. A well-designed data infrastructure makes evidence-based decision-making visible and fosters innovation.

According to the articles analyzed herein, the information regarding the key drivers for building a data culture can be grouped as followed:

4.7. Data Analytics

This driver involves descriptive, diagnostic, prescriptive, and predictive analytics, which aid in strategic and operational decision-making, providing insights into what might happen in the future or identifying the underlying cause of a problem. Analytics offers a combination of technology and techniques that efficiently and effectively address new or existing problems (Uddin Murad et al., 2022; Verma & Bhattacharyya , 2017). Analysis involves the collection, organization, and analysis of massive amounts of data to uncover patterns and information (Ngo et al., 2020).

Analytics can be classified into four main types. *Descriptive analytics* forecasts future skills and trends, offering insights into what might happen (Riahi et al., 2018). It answers the question: What is happening? This represents a preliminary stage of data processing, which also allows for the creation of a historical dataset.

Diagnostic analysis allows one to ask, “Why is this happening?” It helps in the search for the root cause of a problem. Such analysis attempts to find or understand the causes of events and behaviors. It also helps in understanding the connections between the different types of data that may be present in an organization (Ngo et al., 2020).

Predictive analytics examines data to make predictions (Riahi et al., 2018; Sivarajah et al., 2017). It allows us to answer the question “What is likely to happen?” and uses historical data to predict the future. It relies on data mining and artificial intelligence to analyze current data and develop probable scenarios.

Prescriptive analytics provides support for decision-making and performance improvement. It focuses on discovering the optimal solution to consider and guiding the organization on how to solve a problem appropriately (Gasimova, 2016)and the basic characteristics and features of big data.”,”container-title”:”Problems of Information Technology”,”DOI”:”10.25045/jpit.v07.i1.09”,”ISSN”:”20774001, 23040157”,”issue”:”1”,”journalAbbreviation”:”JPIT”,”language”:”en”,”page”:”62-78”,”source”:”DOI.org (Crossref.

4.8. Democratization of Data

One of the most important factors in fostering a data-driven culture is promoting data democracy. This fosters shared responsibility at all levels of an organization (Chatterjee et al., 2024). Through this practice, an organization can improve its ability to collect, process, and analyze data to reach critical conclusions and make efficient decisions without the influence of external forces or pressures (Marinakis et al., 2021).

In this key regard, one can also refer to data governance, which is defined as the set of decision rights, processes, standards, policies, and technologies required to manage, maintain, and leverage information as a business resource. The primary goal here is to build a stronger data culture. This also ensures that appropriate procedures and processes are in place, together with a secure infrastructure, while protecting and managing individual data elements efficiently.

The successful implementation of governance has a comprehensive practical effect on an organization’s performance, providing a long-term tool that also contributes to reducing repeated work. A successful transition to data democratization requires sharing of data within the organization, thereby developing better knowledge to achieve objectives and create value (Verma & Bhattacharyya, 2017; C. Chen, 2022; Tvedt et al., 2023). Authors such as Connelly et al., (2012) and Barker Scott & Manning (2021)success has been elusive. It is becoming clear that in many instances employees are unwilling to share their knowledge even when organizational practices are designed to facilitate transfer. Consequently, this paper develops and investigates a novel construct, knowledge hiding. We establish that knowledge hiding exists, we distinguish knowledge hiding from related concepts (knowledge hoarding and knowledge sharing indicate that data exchange facilitates the consultation process and, once it is made accessible, digital transformation becomes possible.

4.9. Data-Driven and Knowledge-Based Leadership

The leader’s role is fundamental regarding the establishment of a data-driven culture within an organization (Connely et al., 2000; Bowers et al., 2017; C. Chen, 2022)”given”:”S”},{“family”:”Threlfall”,”given”:”K”},{“family”:”Marks”,”given”:”M”},{“-family”:”Mumford”,”given”:”M”}],”issued”:{“date-parts”:[[“2000”]]}}},{“id”:469,”uris”:[“http://zotero.org/users/local/Uiz1lDAK/items/HGXGGJXC”],”itemData”:{“id”:469,”type”:”article-journal”,”abstract”:”Most organizations faced with a crisis will rely on the leader in place at that time to lead them out of the crisis, often with disastrous results. When the crisis gets out of hand, these organizations realize belatedly that the current leader does not necessarily possess the leadership style required to manage the crisis effectively. We present three crisis response leadership principles (CRLP. Successfully implementing data-driven decision-making requires skills such as focusing on high-value challenges (Sivarajah et al., 2017), which allows for an alignment of analytics with a significant organizational challenge (Ngo et al., 2020), thus making it easier to overcome both managerial and cultural obstacles.

Likewise, leaders should prioritize the definition of necessary insights and questions to achieve business objectives, as opposed to simply collecting available data. Furthermore, data literacy helps them understand, analyze, and reason with data, which allows the translation of knowledge into significant improvements.

Knowledge management is a meticulous process that relies on strategies for acquiring and creating knowledge, as well as how it is shared within an organization and how it is applied (Nonaka, 1994; Nahapiet & Ghoshal, 1998; Alavi & Denford, 2011; Al-Busaidi & Olfman, 2017)organizations play a critical role in articulating and amplifying that knowledge. A theoretical framework is developed which provides an analytical perspective on the constituent dimensions of knowledge creation. This framework is then applied in two operational models for facilitating the dynamic creation of appropriate organizational knowledge.]”,”archive”:”JSTOR”,”container-title”:”Organization Science”,”ISSN”:”10477039, 15265455”,”issue”:”1”,”note”:”publisher: INFORMS”,”page”:”14-37”,”title”:”A Dynamic Theory of Organizational Knowledge Creation”,”volume”:”5”,”author”:[{“family”:”Nonaka”,”given”:”Ikujiro”}],”issued”:{“date-parts”:[[“1994”]]}}},{“id”:1587,”uris”:[“http://zotero.org/users/local/Uiz1lDAK/items/BUZG7X38”],”itemData”:{“id”:1587,”type”:”article-journal”,”abstract”:”Scholars of the theory of the firm have begun to emphasize the sources and conditions of what has been described as \”the organizational advantage,\” rather than focus on the causes and consequences of market failure. Typically, researchers see such organizational advantage as accruing from the particular capabilities organizations have for creating and sharing knowledge. In this article we seek to contribute to this body of work by developing the following arguments: (1. Knowledge-oriented leaders foster learning environments and make decisions based on up-to-date data. A knowledge-oriented leader (Bowers et al., 2017) can positively moderate the relationship between an organization's capabilities and its ability to often with disastrous results. When the crisis gets out of hand, these organizations realize belatedly that the current leader does not necessarily possess the leadership style required to manage the crisis effectively. We present three crisis response leadership principles (CRLPrespond to problems or challenges.

Numerous studies (Abdullahi et al., 2020; Correa et al., 2019; Hashim et al., 2025) democratic and transformational leadership styles on employees' organizational citizenship behavior (OCBhave highlighted that leadership support is linked to the development of knowledge-sharing activities between organizations and employees. This, in turn, fosters trust among employees and helps to reduce costs (Singh et al., 2019)research on how entrepreneurial orientation impacts the relationship between grassroots innovation (GRI. With effective leadership (Al-Busaidi & Olfman, 2017; Baesens et al., 2016; Goleman et al., 2002; Iorio et al., 2017), employees voluntarily share their ideas and experiences with colleagues, contributing to knowledge sharing. Creating knowledge through empowerment fosters an environment of trust and belief among employees, leading to a process of contributing new ideas and, consequently, innovation.

This process of cultural transformation, which stems from the trust inherent in the transfer of ideas, facilitates a shift towards data-driven decision-making. This is why, according to J. Chen et al., (2006) and Darmaningrat et al., (2019), knowledge management and leadership communication are important attributes that drive data-driven leadership.

Effective leadership communication is a skill that every leader must develop to operate efficiently. It allows them to influence employee attitudes, provide motivation, and ultimately achieve organizational goals. To accomplish this, leaders must share and respond to information promptly, listen to others' perspectives, and communicate clearly and precisely at all levels of the organization.

4.10. Creating a Data-Driven Culture

Creating a data-driven culture is essential for organizations seeking to leverage the full potential of data in decision-making (Brynjolfsson et al., 2011; Bratasanu, 2018; Chenchu et al., 2025)we find that firms that adopt DDD have output and productivity that is 56% higher than what would be expected given their other investments and information technology usage. Furthermore, the relationship between DDD and performance also appears in other performance measures such as asset utilization, return on equity and market value. Using instrumental variables methods, we find evidence that the effect of DDD on the productivity do not appear to be due to reverse causality. Our results provide some of the first large scale data on the direct connection between data-driven decision making and firm performance.”,”container-title”:”SSRN Electronic Journal”,”DOI”:”10.2139/ssrn.1819486”,”ISSN”:”1556-5068”,”journalAbbreviation”:”SSRN Journal”,”language”:”en”,”source”:”DOI.org (Crossref. In an organizational environment characterized by accelerated dynamism and unprecedented data generation, it is no longer sufficient for leaders to simply use data for decision-making; rather, cultivating an organizational culture that prioritizes data at all levels is essential.

This means that the organization can equip employees with the tools required to use data, prioritize them, and base their actions and decisions on them. However, establishing a data-driven culture requires a planned process, appropriate technology, and consistent leadership support to ensure that data and information become an essential component of processes and are properly integrated throughout the organization. This allows organizations to improve their decision-making capabilities, foster innovation, and gain a competitive advantage.

Data literacy across the organization (Peng et al., 2011; Bratasanu, 2018; Esposito et al., 2024; Nisar et al., 2021) allow decision makers (DMsis an essential step for a data-driven culture to permeate all levels of a business. The data-rich environment in which organizations now operate means that employees at all levels must be able to read, interpret, and communicate data effectively. These skills are increasingly essential for better decision-making, as well as for improving efficiency and achieving company objectives.

To achieve data literacy, a comprehensive training plan is needed, tailored to all employee experience levels. This plan should cover basic concepts, data comprehension, statistics, and data visualization. For more experienced employees, topics such as data analysis tools, interpreting complex datasets, and applying the information obtained could also be included.

Leadership plays a vital role in data literacy because, when leaders prioritize this, they send a clear message to the rest of the organization by demonstraging decision-making and encouraging others to adopt similar practices. Furthermore, they must provide the resources necessary to ensure access to information for informed decision-making.

4.11. Decision-Making Process

In today's dynamic business environment, the decision-making process needs data as an essential driver of informed decisions (Helfat & Peteraf, 2009; Abbasi et al., 2016). This implies the ability to interpret, analyze, and translate data into meaningful insights that guide the achievement of the organization's strategic objectives.

Successful decision-making requires the transformation of data into useful information, as unprocessed data have no practical value. Therefore, to leverage data, organizations must convert them into valuable information that guides business objectives. Once data are structured, they must be analyzed to uncover patterns and correlations. This process involves using models and different types of analysis, such as those mentioned above.

Transforming data into useful information requires a collaborative approach (Barker Scott & Manning, 2021; C. Chen, 2022), since sharing and debating information ensures its interpretation from multiple perspectives, leading to more complete and balanced decisions that are not isolated but rather as strategic as possible.

In complex situations, decision-making frameworks (Layden et al., 2024; Chenchu et al., 2025) can be applied to provide a structured approach that helps leaders navigate complex situations more effectively. These frameworks allow for the evaluation of different options and the differentiation of potential outcomes to select the best course of action on the basis of the data available.

From this perspective, rational decision-making is based on the premise that decisions are made through a logical–sequential process, which involves defining the problem, gathering information, identifying alternatives, evaluating options, and choosing the most appropriate one. This process is useful when all relevant information is available and outcomes can be predicted with a reasonable degree of certainty. This method allows a leader to ensure that the chosen decision is supported by evidence.

Another, more intuitive model emphasizes the role of experience and intuition in the decision-making process. This can be effective in situations where complete information is lacking but quick decisions are needed. The experienced leader can make judgments on the basis of their prior knowledge. This approach can be fast, but it lacks depth and rigor, making it suitable for situations where time is of the essence.

These decision frameworks are tools for managing complexity and, to some extent, reducing uncertainty. Depending on the situation, one or more frameworks can be used to structure the decision-making process. It is important to choose a decision framework that is appropriate to the nature of the problem, the time available for its resolution, and the data available. Using this approach ensures that decisions are made on the basis of sound analysis.

4.12. Ethics in Data-Driven Decision-Making

Because organizations are increasingly reliant on data to guide their strategies and operations, ethical considerations are relevant. Ensuring the integrity and accuracy of information is a necessary first step in maintaining ethical standards. Data management requires truthful (Campbell & Coff, 2012; Ahmad, 2015) this study attempts to develop a model for successful BI deployment and empirically examines the association between BI deployment and sustainable competitive advantage. Taking the telecommunications industry in Malaysia as a case example, the research particularly focuses on the influencing perceptions held by telecommunications decision makers and executives on factors that impact successful BI deployment. The research further investigates the relationship between successful BI deployment and sustainable competitive advantage of the telecommunications organizations. Another important aim of this study is to determine the effect of moderating factors such as organization culture, business strategy, and use of BI tools on BI deployment and the sustainability of firm's competitive advantage. This research uses combination of resource-based theory and diffusion of innovation (DOIand impartial information. If data are manipulated or altered in any way, decisions based on them can lead not only to flawed strategies but also to resource misallocation and potentially harmful consequences.

Therefore, robust data validation processes are required to confirm that the information used is accurate and reliable, thus maintaining trust among stakeholders. Privacy and security are other important ethical considerations in decision-making. Organizations must comply with privacy regulations and adopt best practices for data protection.

The ethical use of data in decision-making is more than just securing and protecting them; it involves ensuring that data are used fairly and transparently, so as not to reinforce biases (Bratasanu, 2018; Marinakis et al., 2021; Alaimo & Kallinikos, 2022; Chenchu et al., 2025). The leader's role in this regard involves acknowledging and identifying potential biases, as these can arise from historical inequalities or biased data collection practices. When misused, data can perpetuate discriminatory practices and lead to decisions that harm individuals from specific groups.

Ethical leadership in decision-making requires leaders to minimize bias and promote equity so that their decisions contribute positively to society. By considering ethical practices within data-driven practices, it is possible to build a responsible and transparent organization that cares not only about the data it collects but also about the people it serves.

4.13. The Four Drivers and Organizational Leadership

The findings of this study highlight that building a data-driven culture can be influenced by four essential drivers: data analytics, data democratization, data-driven and knowledge-based leadership, and culture creation. To understand the organizational scope of this, it is relevant to analyze how these drivers relate to the most influential leadership styles.

First, data analytics has a natural affinity with transformational and adaptive leadership. Transformational leadership, as Bass & Riggio (2005) argue, promotes innovation, strategic vision, and the development of new capabilities—elements that are essential for the consolidated implementation of advanced analytics practices. Furthermore, adaptive leadership, as analyzed by Heifetz & Linsky (2017), emphasizes experimentation, continuous learning, and the ability to respond in dynamic environments, which also aligns with the demands of analysis in changing contexts.

Data democratization, understood as equitable and timely access to information at all levels of an organization, is clearly supported by transformational leadership, as it promotes trust and empowers employees (Bass & Riggio, 2005). Meanwhile, adaptive leadership helps to encourage collaboration, as well as a joint interpretation of evidence and the ability of teams to use information appropriately. This allows data democratization to become a cultural, technical, and relational process that can expand learning capacity and informed action.

The third driver, related to data-driven and knowledge-based leadership, involves promoting transparency, ethics, and informed decision-making. Transformational leadership is known to motivate employees to adopt a knowledge-driven mindset with analytical rigor. Technological leadership ensures the flow of knowledge, as well as promoting its proper storage and serving as a basis for strategic action (Mikalef et al., 2020).

The fourth driver, which leads to the creation of a data culture, demands leadership that combines vision, coherence, and strategic direction. This is closely aligned with transformational leadership, since its ability to generate a shared vision and reinforce behaviors aligned with this contributes directly to the consolidation of such a culture (Wamba et al., 2017).

5. Conclusions

This bibliometric analysis combined with a systematic literature review revealed that the accelerated shift toward data-intensive organizations poses significant ethical challenges. The generation of massive amounts of information, along with the capacity to process it using analytical tools, entails risks related to transparency, privacy, and data interpretability, as well as automated decision-making. This, coupled with information overload, can lead to confusion, hasty decisions, or delegation of judgments to information systems, necessitating a reevaluation of the role of ethics in data management as a structural component that contributes to the consolidation of an evidence-based culture.

In this context, leadership emerges as an integral element of the four drivers. Adaptive, transformational, and technological leadership styles enable the articulation of a strategic vision that promotes not only the responsible use of information but also the development of analytical capabilities within teams. Leaders act not only as facilitators of access to and adoption of technology but also as ethical mediators. Building a data-driven culture will therefore depend not only on the available infrastructure and processes but also on the leadership's capacity to guide the organization toward meaningful, strategic, and ethical use of information.

Without leaders who drive the use of data to support the digital transformation process, no organization will be able to achieve the level of operational efficiency necessary for consistent improvement in results. Commitment and continuous communication from management are crucial characteristics for shaping team relationships and facilitating shared organizational goals.

Data-driven management contributes to improving knowledge management practices, enabling organizations to gain a competitive advantage by gathering information from both internal and external sources. A significant challenge in data-driven decision-making can be information overload. This can overwhelm leaders with the sheer volume of data they must process, hindering the identification of relevant information and potentially leading to decision paralysis. Therefore, it becomes essential to develop processes and support systems for prioritizing data on the basis of their relevance to a specific decision-making process.

Despite the recognition of the value of analytics, a lack of widespread adoption remains an obstacle stemming from the managerial and cultural framework. Furthermore, the primary barrier is often a lack of understanding of how to use analytics to improve the business. This is further compounded by the challenge of competing priorities at the management level and a culture that discourages information sharing.

Leaders who foster a culture of continuous learning and the adoption of a data-driven culture will be better equipped to face future complexities. A balance between data, human judgment, and ethical principles is required for optimal decision-making, enabling an organization to remain relevant, current, and essential to society and its business environment.

The findings of this study also highlight that the four driving factors of a data-driven culture, which form a dynamic system, do not function in isolation but rather combine to create the conditions necessary for data to become a strategic resource: one that informs decisions and transforms processes but also demands new team competencies. A data-driven culture allows for the convergence of values, skills, governance structure, and leadership practices.

The study confirms that data analytics, information democratization, data-driven leadership, and a data culture are essential pillars for moving toward truly evidence-based organizations. The coherent integration of these four drivers enables organizations to address the challenges arising from informational complexity and fosters more responsible, ethical, and strategic decision-making. However, it is acknowledged that consolidating this approach requires a leadership that is capable of guiding cultural transformation and mitigating the risks associated with data overload, which defines the scope of the study and opens opportunities for future research.

5.1. Implications and Gaps

The results allow us to identify several implications for research and practice:

There is an opportunity to explore how leadership styles (transformational, transactional, and situational, among others) affect the effectiveness of analytics and artificial intelligence in the organizational context.

The literature still treats data culture and leadership as separate fields, revealing the need for integrative conceptual frameworks that explain how leadership styles contribute in a complementary way to the development of analytical capabilities, the governance of information access, and the strengthening of evidence-based organizational practices. This opens an opportunity to move toward more robust models that allow the conceptualization of data maturity as a fluid process mediated by cognitive, cultural, and ethical factors.

From a practical standpoint, organizations that promote data-driven strategic leadership can accelerate the adoption of technologies, fostering innovation and thereby strengthening organizational resilience—a topic that warrants further study in the future.

Finally, the study reveals significant gaps that open the door to future research. A methodological limitation in the literature is identified as the almost complete lack of information derived from longitudinal studies. Likewise, there are few studies addressing the phenomenon of information overload in greater depth, although this is a critical topic for understanding the risks and responsibilities associated with data-driven organizations.

The results should be interpreted considering the limitations inherent in bibliometric studies, particularly the use of a single database and the selection criteria applied, which limit the scope of the analysis on data-driven culture and leadership styles.

References

Abbasi, A., Sarker, S., University of Virginia, Aalto University, Chiang, R., & University of Cincinnati. (2016). Big Data Research in Information Systems: Toward an Inclusive Research Agenda. *Journal of the Association for Information Systems* , *17* (2), I-XXXII. https://doi.org/10.17705/1jais.00423

Abdullahi, AZ, Anarfo, EB, & Anyigba, H. (2020). The impact of leadership style on organizational citizenship behavior: Does leaders' emotional intelligence play a moderating role? *Journal of Management Development* , *39* (9/10), 963-987. https://doi.org/10.1108/JMD-01-2020-0012

Agrawal, R., Wankhede, V.A., Kumar, A., & Luthra, S. (2023). A systematic and network-based analysis of data-driven quality management in supply chains and proposed future research directions. *The TQM Journal* , *35* (1), 73-101. https://doi.org/10.1108/TQM-12-2020-0285

Ahmad, A. (2015). Business Intelligence for Sustainable Competitive Advantage. In *Sustaining Competitive Advantage Via Business Intelligence, Knowledge Management, and System Dynamics* (Vol. 22A, pp. 3-220). Emerald Group Publishing Limited. https://doi.org/10.1108/S1069-096420150000022014

Akhtar, P., Frynas, J.G., Mellahi, K., & Ullah, S. (2019). Big Data-Savvy Teams' Skills, Big Data-Driven Actions and Business Performance. *British Journal of Management* , *30* (2), 252-271. https://doi.org/10.1111/1467-8551.12333

Alaimo, C., & Kallinikos, J. (2022). Organizations Decentered: Data Objects, Technology and Knowledge. *Organization Science* , *33* (1), 19-37. https://doi.org/10.1287/orsc.2021.1552

Alavi, M., & Denford, J. (2011). *Knowledge Management: Process, Practice, and Web 2.0* (pp. 105-124). https://doi.org/10.1002/9781119207245.ch6

Al-Busaidi, K.A., & Olfman, L. (2017). Knowledge sharing through inter-organizational knowledge sharing systems. *VINE Journal of Information and Knowledge Management Systems* , *47* (1), 110-136. https://doi.org/10.1108/VJIKMS-05-2016-0019

Baesens, B., Bapna, R., Marsden, JR, Vanthienen, J., KU Leuven, BELGIUM, & Zhao, JL (2016). Transformational Issues of Big Data and Analytics in Networked Business. *MIS Quarterly* , *40* (4), 807-818. https://doi.org/10.25300/MISQ/2016/40:4.03

Barker Scott, B.A., & Manning, M.R. (2021). Designing for Collaboration: Don't Just Focus on the Team, Focus Also on the Context in Which Teams Work. In AB (Rami) Shani & DA Noumair (Eds.), *Research in Organizational Change and Development* (Vol. 29, pp. 173-199). Emerald Publishing Limited. https://doi.org/10.1108/S0897-301620210000029008

Barros-Contreras, I., Morales-Serazzi, M., Torres-Toukoumidis, A., & Palma-Ruiz, JM (2022). Knowledge Integration and Organizational Performance of Data Analytics in the Family Business. *Journal of Open Innovation: Technology, Market, and Complexity* , *8* (3), 135. https://doi.org/10.3390/joitmc8030135

Bass, B., & Riggio, R. (2005). Transformational leadership: Second edition. In *Transformational Leadership: Second Edition*. https://doi.org/10.4324/9781410617095

Bowers, M.R., Hall, JR, & Srinivasan, M.M. (2017). Organizational culture and leadership style: The missing combination for selecting the right leader for effective crisis management. *Business Horizons* , *60* (4), 551-563. https://doi.org/10.1016/j.bushor.2017.04.001

Bratasanu, V. (2018). Leadership decision-making processes in the context of data driven tools. *Quality - Access to Success* , *19* , 77-87.

Brynjolfsson, E., Hitt, L.M., & Kim, H.H. (2011). Strength in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance? *SSRN Electronic Journal* . https://doi.org/10.2139/ssrn.1819486

Campbell, B., & Coff, R. (2012). *(Campbell, Coff & Kryscynski, 2012)—Rethinking Sustained Competitive Advantage.pdf* .

Carillo, K.D.A. (2017). Let's stop trying to be "sexy" – preparing managers for the (big) data-driven business era. *Business Process Management Journal* , *23* (3), 598-622. https://doi.org/10.1108/BPMJ-09-2016-0188

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2024). Does data-driven culture impact innovation and performance of a firm? An empirical examination. *Annals of Operations Research* , *333* (2-3), 601-626. https://doi.org/10.1007/s10479-020-03887-z

Chen, C. (2022). Influence of big data analytical capability on new product performance – the effects of collaboration capability and team collaboration in high-tech firm. *Chinese Management Studies* . https://doi.org/10.1108/CMS-02-2022-0053

Chen, J., Silverthorne, C., & Hung, J. (2006). Organization communication, job stress, organizational commitment, and job performance of accounting professionals in Taiwan and America. *Leadership & Organization Development Journal* , *27* (4), 242-249. https://doi.org/10.1108/01437730610666000

Chenchu, M. K., Ruikar, K., & Jha, K. N. (2025). *A network-based framework for enhancing data integration and usage in highway infrastructure decision-making* .

Cheong, H. W. (2016). Management of Technology Strategies Required for Major Semiconductor Manufacturer to Survive in Future Market. *Procedia Computer Science* , *91* , 1116-1118. https://doi.org/10.1016/j.procs.2016.07.163

Connelly, C.E., Zweig, D., Webster, J., & Trougakos, J.P. (2012). Knowledge hiding in organizations. *Journal of Organizational Behavior* , *33* (1), 64-88. https://doi.org/10.1002/job.737

Connely, M., Gilbert, J., Zaccaro, S., Threlfall, K., Marks, M., & Mumford, M. (2000). Exploring the relationship of leadership skills and knowledge to leader performance." *Leadership Quarterly* , *11* (1), 65-86.

Correa, A., Benjumea, M., & Valencia, A. (2019). Knowledge management: An alternative to solve educational problems. *Educare Electronic Magazine* , *23* (2), 1-27. https://doi.org/10.15359/ree.23-2.1

Darmaningrat, EWT, Muqtadiroh, FA, & Bukit, TA (2019). Communication management plan of ERP implementation program: A case study of PTPN XI. *Procedia Computer Science* , *161* , 359-366. https://doi.org/10.1016/j.procs.2019.11.134

Demirezen, MU, & Navruz, TS (2023). Performance Analysis of Lambda Architecture-Based Big-Data Systems on Air/Ground Surveillance Application with ADS-B Data. *Sensors* , *23* (17), 7580. https://doi.org/10.3390/s23177580

Dubey, R., Gunasekaran, A., Childe, S., Blome, C., & Papadopoulos, T. (2019). Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture. *British Journal of Management* , *30* , 341-361. https://doi.org/10.1111/1467-8551.12355

Esposito, P., Antonucci, G., Palozzi, G., & Fijałkowska, J. (2024). Cognitive systems for improving decision-making in the workplace: An explorative study within the waste management field. *Management Decision*. https://doi.org/10.1108/MD-08-2023-1320

Fawcett, T., & Provost, F. (2013). *Data Science for Business* .

Fothergill, B.T., Knight, W., Stahl, B.C., & Ulnicane, I. (2019). Responsible Data Governance of Neuroscience Big Data. *Frontiers in Neuroinformatics* , *13* , 28. https://doi.org/10.3389/fninf.2019.00028

Gasimova, R. (2016). «BIG DATA» ANALYTICS: AVAILABLE APPROACHES, PROBLEMS AND SOLUTIONS. *Problems of Information Technology* , *07* (1), 62-78. https://doi.org/10.25045/jpit.v07.i1.09

Ghafoori, A., Gupta, M., Merhi, M.I., Gupta, S., & Shore, A.P. (2024). Toward the role of organizational culture in data-driven digital transformation. *International Journal of Production Economics* , *271* , 109205. https://doi.org/10.1016/j.ijpe.2024.109205

Goleman, D., R, B., & McKee, A. (2002). *The New Leaders: Transforming the art of leadership into the science of results* . Little Brown.

Hashim, MA, Che Ibrahim, CKI, Jaafar, NAL, Kordi, NE, Haron, AT, & Umeokafor, N. (2025). Building data driven culture for digital competitiveness in construction industry: A theoretical exploration. *International Journal of Construction Management* , *25* (3), 334-346. https://doi.org/10.1080/15623599.2024.2322237

Heifetz, R.A., & Linsky, M. (2017). *Leadership on the line: Staying alive through the dangers of change* (Revised edition). Harvard Business Review Press.

Helfat, C.E., & Peteraf, M.A. (2009). Understanding dynamic capabilities: Progress along a developmental path. *Strategic Organization* , *7* (1), 91-102. https://doi.org/10.1177/1476127008100133

Huynh, M.-T., Nippa, M., & Aichner, T. (2023). Big data analytics capabilities: Patchwork or progress? A systematic review of the status quo and implications for future research. *Technological Forecasting and Social Change*, *197*, 122884. https://doi.org/10.1016/j.techfore.2023.122884

Iorio, R., Labory, S., & Rentocchini, F. (2017). The importance of pro-social behavior for the breadth and depth of knowledge transfer activities: An analysis of Italian academic scientists. *Research Policy* , *46* (2), 497-509. https://doi.org/10.1016/j.respol.2016.12.003

Korherr, P., Kanbach, D.K., Kraus, S., & Mikalef, P. (2022). From intuitive to data-driven decision-making in digital transformation: A framework of prevalent managerial archetypes. *Digital Business* , *2* (2), 100045. https://doi.org/10.1016/j.digbus.2022.100045

Krippendorff, K. (2013). *Content Analysis an Introduction to Its Methodology* (Fourth Edition). SAGE Publications Ltd.

Kumar, R. (2025). A Bibliometric Analysis on Organizational Culture and Intention to Leave Using Visualizing Network. *Journal of Informatics Education and Research* , *5* (2).

Kumari, M. B. (2019). Developing entrepreneurial skills. *International Journal of Recent Technology and Engineering* , *8* (2 Special Issue 4), 617-620. https://doi.org/10.35940/ijrte.B1122.0782S419

Layden, T., Gulbransen, K., & Lightbown, S. (2024). Using a knowledge translation framework for effective interprofessional leadership: A nursing student perspective. *Nurse Education Today* , *133* , 106035. https://doi.org/10.1016/j.nedt.2023.106035

López-Figueroa, JC, Ochoa-Jiménez, S., Palafox-Soto, MO, & Sujey Hernandez Munoz, D. (2025). Digital Leadership: A Systematic Literature Review. *Administrative Sciences* , *15* (4), 129. https://doi.org/10.3390/admsci15040129

Lycett, M. (2013). 'Datafication': Making sense of (big) data in a complex world. *European Journal of Information Systems* , *22* (4), 381-386. https://doi.org/10.1057/ejis.2013.10

Marinakis, V., Koutsellis, T., Nikas, A., & Doukas, H. (2021). AI and Data Democratization for Intelligent Energy Management. *Energies* , *14* (14), 4341. https://doi.org/10.3390/en14144341

Massaroni, Enrico, Cozzolino, Alessandra, & Wankowicz, Ewa. (2018). Sustainability in supply chain management—A literature review. *Sinergie Italian Journal of Management* , *98* , 331-355. https://doi.org/10.7433/s98.2015.19

Mikalef, P., & Krogstie, J. (2019). Investigating the Data Science Skill Gap: An Empirical Analysis. *2019 IEEE Global Engineering Education Conference (EDUCON)* , 1275-1284. https://doi.org/10.1109/EDUCON.2019.8725066

Nahapiet, J., & Ghoshal, S. (1998). Social Capital, Intellectual Capital, and the Organizational Advantage. *The Academy of Management Review* , *23* (2), 242-266. JSTOR. https://doi.org/10.2307/259373

Ngo, J., Hwang, B.-G., & Zhang, C. (2020). Factor-based big data and predictive analytics capability assessment tool for the construction industry. *Automation in Construction* , *110* , 103042. https://doi.org/10.1016/j.autcon.2019.103042

Nisar, QA, Nasir, N., Jamshed, S., Naz, S., Ali, M., & Ali, S. (2021). Big data management and environmental performance: Role of big data decision-making capabilities and decision-making quality. *Journal of Enterprise Information Management* , *34* (4), 1061-1096. https://doi.org/10.1108/JEIM-04-2020-0137

Nonaka, I. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Organization Science* , *5* (1), 14-37. JSTOR.

Nwachukwu, C., & Hieu, V. M. (2021). Digital Transformation Adoption: Antecedents and Consequences. In J. Metselaar (Ed.), *Strategic Management in the Age of Digital Transformation* . Proud Pen. https://doi.org/10.51432/978-1-8381524-3-7_2

Oliver, G., Cranefield, J., Lilley, S., & Lewellen, M. (2023). Data Cultures: A scoping literature review. *Information Research an International Electronic Journal* , *28* (1), 3-29. https://doi.org/10.47989/irpaper950

Peng, Y., Zhang, Y., Tang, Y., & Li, S. (2011). An incident information management framework based on data integration, data mining, and multi-criteria decision making. *Decision Support Systems* , *51* (2), 316-327. https://doi.org/10.1016/j.dss.2010.11.025

Riahi, Y., Riahi, S., & Department of Mathematics and Computer Science, Faculty of Sciences, University of ChouaibDoukkali Jabran Khalil JabranAvenu , El jadida 24000, Morocco. (2018). Big Data and Big Data Analytics: Concepts, types and technologies. *International Journal of Research and Engineering* , *5* (9), 524-528. https://doi.org/10.21276/ijre.2018.5.9.5

Sağbaş, M., & Erdoğan, F.A. (2022). DIGITAL LEADERSHIP: A SYSTEMATIC CONCEPTUAL LITERATURE REVIEW. *Digital Leadership* .

Salerno, FF, & Maçada, ACG (2025). Data-driven culture and orchestrated data ecosystems: A conceptual model based on the resource-based view. *Gestão Magazine* , *32* (2), 123-135. https://doi.org/10.1108/REGE-12-2024-0184

Singh, S.H., Bhowmick, B., Eesley, D., & Sindhav, B. (2019). Grassroots innovation and entrepreneurial success: Is entrepreneurial orientation a missing link? *Technological Forecasting and Social Change* , *February* , 119582. https://doi.org/10.1016/j.techfore.2019.02.002

Sivarajah, U., Kamal, M.M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, *70*, 263-286. https://doi.org/10.1016/j.jbusres.2016.08.001

Tvedt, I.M., Tommelein, I.D., Klakegg, O.J., & Wong, J.-M. (2023). Organizational values in support of leadership styles fostering organizational resilience: A process perspective. *International Journal of Managing Projects in Business* , *16* (2), 258-278. https://doi.org/10.1108/IJMPB-05-2022-0121

Uddin Murad, M.A., Cetindamar, D., & Chakraborty, S. (2022). Identifying the Key Big Data Analytics Capabilities in Bangladesh's Healthcare Sector. *Sustainability*, *14* (12), 7077. https://doi.org/10.3390/su14127077

Verma, S., & Bhattacharyya, S.S. (2017). Perceived strategic value-based adoption of Big Data Analytics in emerging economy: A qualitative approach for Indian firms. *Journal of Enterprise Information Management* , *30* (3), 354-382. https://doi.org/10.1108/JEIM-10-2015-0099

Vidgen, R., Shaw, S., & Grant, D. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*. https://doi.org/10.1016/j.ejor.2017.02.023

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J., Dubey, R., & Childe, S.J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70* , 356-365. https://doi.org/10.1016/j.jbusres.2016.08.009