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Research Article

A Systematic Review of Exploring the Multiple Dimensions of Data-Driven Culture

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ABSTRACT

Data-driven culture refers to the set of values, behaviors, and practices within the organization that prioritize the effective use of data. The role of data-driven culture in improving organizational outcomes is widely recognized. Despite its growing importance, a holistic view of data-driven culture, which could guide practitioners and researchers, is still lacking. This review paper aims to develop an integrative framework for understanding the multiple dimensions of data-driven culture and its relationship. This study conducts a domain-based systematic literature review to discern the breadth and depth of data-driven culture as portrayed in prior studies published between 2000-2024. The Preferred Reporting System for Systematic Literature Review and Meta-Analyses (PRISMA-SLR) protocol identified 32 primary studies in healthcare, business organizations, and educational institutions indexed in Web of Science and Scopus, along with grey literature sourced via Google. This study uncovers the multiple dimensions of data-driven culture including data-driven mindset, data-driven leadership, data literacy, data accessibility, and data governance, and its influence on decision-making practices within the organization. This review further highlights the interrelationships between multiple dimensions of data-driven culture and provides an integrative framework for leaders and managers to build data-driven organizations. Additionally, this review identifies actionable insights and research gaps for further exploration.

INTRODUCTION

In times of a complex and turbulent business environment, making timely and informed decisions is an absolute necessity to achieve agility and high organizational performance (Ghafoori et al., 2024; Kitchens et al., 2018; Medeiros & Macada, 2022; Rane & Narvel, 2022). Scholars, business practitioners, and policymakers have stressed the importance of data-driven decision-making for continual business growth, identifying and understanding complex business processes and interdependencies, exploring new business opportunities, and enhancing knowledge and

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innovation to achieve competitive adaptability (Chaudhuri et al., 2024; Himanen et al., 2019; Rachinger et al., 2019; Dubey et al., 2021). Although organizations gain high performance and operational efficiencies from data-driven decisions, many decisions are based on intuition and experience (Barends et al., 2017). It was found in prior studies that technological investments failed to yield desired outcomes when organizations did not foster a data-driven culture (Barton and Court, 2012). The New Vantage Partners Survey (2022) which tracks the progress of Fortune 1000 companies and industry leaders to lead corporate transformation initiatives with a focus on building a data-driven organization, reported that 91.9% of executives cite cultural obstacles (lack of organizational alignment, poor data literacy, cultural resistance, people mindset, and inefficient process) as the greatest stumbling blocks to become data-driven organizations despite their heavy investments in technology and analytics. Bean (2022) in his article reported that companies have worked hard to become data-driven, but perpetually underestimate the significance of the cultural change that nurtures the ability of the people and organization to adapt to change.

Prior researchers suggested that organizations need to cultivate a data-driven culture and reframe the values, assumptions, norms, mindset, philosophies, and ideologies to create value from the data for improved decision-making, optimize resource allocation, boost employees' motivation and engagement, encourage agility and experimentation, and increase business performance (Busse, 2012; Echevarria et al., 2017; Jun et al., 2020). Organizations that cultivate a data-driven culture are twice as likely to exceed their business goals, achieve better competitive advantages, provide quality decisions, enhance process improvement and take quality decisions (Chaudhuri et al., 2024). Although the principles governing the organizational culture are generally universal, such as clear mission and vision, values and ethics, clear communication, empowerment and autonomy, collaboration and teamwork, and continuous learning and improvement- cultivating and nurturing a data-driven culture has a unique aspect that needs to be addressed by organizations (Anderson, 2015; Esteller-Cucala et al., 2020). Practically, a data-driven culture is much more complex than a traditional organizational culture. In general, academic reviews on data-driven culture revealed that transforming legacy culture does not happen overnight. It requires working on all cultural levels, as defined by Schein (2010), basic underlying assumptions, beliefs and values, norms, behaviours, leadership, management, strategy, and organizational capabilities. Therefore, it is essential to understand the different aspects of a data-driven culture since they are interrelated and shape the organization's overall culture.

Similar Reviews: Identifying Gaps

Currently, there is no consensus on a finite set of key dimensions to describe data-driven culture. However, there was some research on specific aspects of data-driven culture such as leadership (Chen, 2020; Lovink et al, 2022) or data infrastructure (Kim & Cho, 2018; Yu et al., 2021), there needs to be more holistic framework that can build up the interactions and relationships between the data-driven culture dimensions. For instance, data-driven culture encompasses diverse dimensions (e.g., people, data, technology, methods), but studies often focus on one or two aspects, leading to unidimensional treatment. Studies like Davenport (2006) and Westerman et al., (2014) focus primarily on leadership and decision-making analytics, neglecting organizational context or employee engagement. Many studies equate the adoption of advanced analytics tools and technologies with the creation of a data-driven culture, overlooking the importance of people, processes, and organizational readiness (Chen, 2020).

Hence, it is crucial to explore the dimensions of data-driven culture and to understand the interconnections between these dimensions to incorporate a data-driven culture framework in organizations for data-driven decision-making. This systematic review addressed the following research question:

- What are the dimensions of data-driven culture and how are they related to each other?

Conceptual Boundaries

Data-driven culture does not have a definitive definition. However, it is often described as a set of values, behaviours, and practices within the organization that prioritize the effective use of data. We also found that some authors refer to it as evidence-based culture (Melnyk et al., 2017), information culture, analytical culture (Popovič et al., 2012), and business intelligence culture (Skyrius et al., 2016). While

there may be subtle differences in emphasis or scope between these terms, they generally fit the broader concept of a data-driven culture where data is at the core of decision-making to improve performance and drive organizational success. Therefore, we did not limit our analysis to data-driven culture only; instead, we also included other related terms such as evidence-based culture and business intelligence culture to provide a more general understanding of different aspects of data culture.

METHODOLOGY

Eligible Study Designs

We covered qualitative, quantitative, and mixed-method studies, and grey literature including, reports, blogs, working papers, newsletters, and webinars. The rationale for including grey literature is to reduce the publication bias in a systematic review to cover the depth and breadth of the review comprehensively (Paez, 2017). Additionally, we aim to broaden the scope of our findings by including relevant materials that may not be covered in scholarly publications (Adams et al., 2017; Rothstein & Hopewell, 2009). It also provides contextual information for why and how the data-driven interventions are effective. It also facilitates the applied researchers and practitioners to identify the dimensions and antecedents of a data-driven culture in real-world scenarios (Adams et al., 2017).

Search Methods

In the systematic literature review, it is essential to select the databases that provide breadth and depth of the specific topic (Gusenbauer & Haddaway, 2020). We searched for peer-reviewed English language articles in the following databases including Web of Sciences (WoS), Scopus, ProQuest, and Google Scholar and the grey literature using websites, online portals, and social media such as LinkedIn. WoS and Scopus are the largest and the comprehensive databases for covering interdisciplinary research. According to Mongeon and Paul-Hus (2016), WoS covers a wide range of disciplines such as social sciences, technology, and health that is appropriate for exploring the data-driven culture. While both databases focus on high-quality peer-reviewed articles, Scopus has the advantage of being the largest database, covering 330 disciplines, indexed 27950 peer-reviewed journals, 2.48 million total book items, 11.6 million conference papers and 49 million patents. The rationale for selecting these databases is their broad coverage, rigorous indexing and high-impact peer-reviewed journals (Singh et al., 2021). Google Scholar provides free access to scholarly documents. It facilitates in identifying the open access and underrepresented studies. The rationale for selecting ProQuest is its focus on practical applications and case studies to capture the practical dimensions of a data-driven culture.

Searches were performed based on different keywords, including the terms data-driven culture, evidence-based culture, information culture, analytical culture and business intelligence culture. We searched the literature of the last 23 years from 2000 to 2023 because in the early 2000s, the concept of evidence-based management was developed to encourage the collection of evidence to make informed decisions. Although the trend was slow in the given era (2000 to 2009) in adopting evidence-based practices, few studies highlighted the significance of incorporating technology, information, organizational structure, method, and process to improve evidence-based decision-making (Collan & Lainema, 2005; Davenport, 2006; Learmonth & Harding, 2006).

Quality Assessment Tools

For the quality appraisal of peer-reviewed articles, we used the Mixed Method Appraisal Tool (MMAT) (Hong et al., 2018). This tool has been extensively used for systematic reviews, including quantitative, qualitative, and mixed-method studies (Shorten & Smith, 2017). The overall quality score was calculated using MMAT and represented as (*) for 20% quality criteria, (**) for 40 %, (***) for 60%, (****) for 80%, and (*****) for 100% quality criteria. For instance, the highest score was given to those quantitative, qualitative, and mixed studies that fulfilled all four criteria such as the appropriateness of research design approach, adequacy of findings, appropriateness of measurement regarding both the interventions and outcomes, appropriateness of statistical analysis, and rationale for research design to address the research questions. For appraising the quality of grey literature, the Accuracy, Authority, Coverage, Objectivity, Date, and Significance (AACODS) checklist was used because it provides a structured framework to assess the quality and credibility of grey literature (Johnson & Vindrola-Padros, 2017). Then findings from grey

literature were integrated with peer-reviewed articles through a thematic coding process. This approach helps to assess whether the findings from grey literature further support, extend or contradict findings from peer-reviewed articles. For example, if peer-reviewed articles identify data-driven leadership as one of the dimensions of DDC then grey literature was analyzed to assess whether it supports or contradicts this finding.

RESULTS & FINDINGS

Study Selection and Study Characteristics

We selected papers based on titles, abstracts, and keywords followed by independent full-text screening by two investigators to assess study relevancy based on pre-determined criteria. We used Mendeley to store and organize the selected studies. Our searches yielded 6234 results. We then identified and eliminated 2428 duplicate studies. The remaining 3806 studies were further screened for eligibility criteria, excluding 3072 studies, and leaving behind 734 studies for retrieval. Furthermore, 512 studies out of 734 were excluded for the following reasons: editorials or commentaries (112), conceptual studies (17), book reviews (5), and others (378) for instance studies published in non-English languages, case descriptions, and discussions. Finally, we reviewed the full text of 222 articles against eligibility.

The two reviewers independently extracted data including title, author(s), year of publication, data collection tools, and associated dimensions of data-driven culture. Initial searches of grey literature yielded 50 records including 44 websites and six government and business reports. We excluded 46 studies that did not meet the AACODS quality appraisal criteria. Finally, we obtained 32 primary articles including 28 peer-reviewed articles, and four studies from grey literature (one report and three websites) for further analysis. The study selection process is summarized in the PRISMA flow diagram (see Figure 1). This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement.

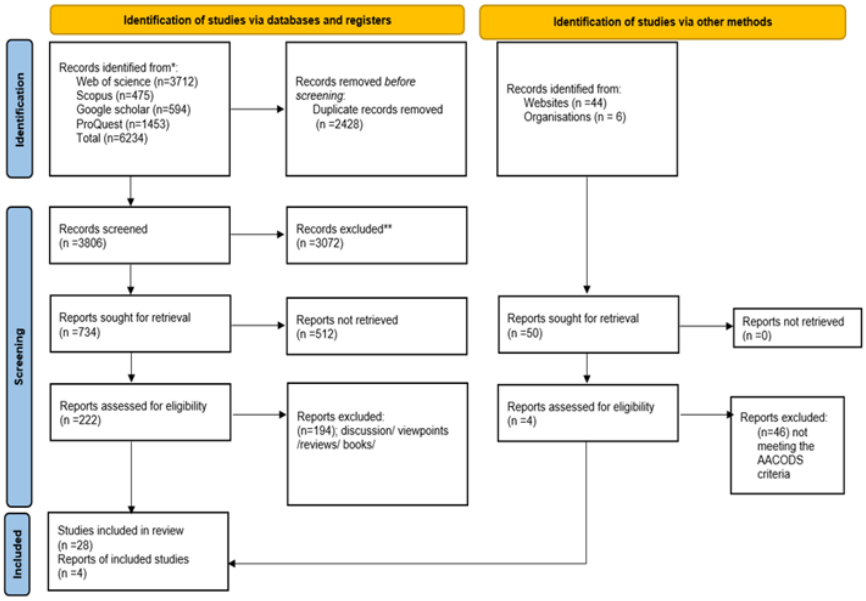

Fig. 1. PRISMA Flow Diagram

Table 1
Inclusion and Exclusion Criteria

Inclusion criteria	Exclusion criteria
Published in peer-reviewed journals	Not in the English language
Explore dimensions of data or evidence as a primary or secondary objective	Opinions, conceptual papers, editorials, discussions, or textbooks
Empirical studies of all design types	Articles not reporting features and characteristics of a data-driven culture
Content published from 2005 to 2022	

Table 2
Number of Studies from Different Countries

Name of Countries	Number of Studies
USA	12
Canada	3
Australia	2
UK	1
China	1
Korea	1
Israel	1
Lebanon	1
Egypt	1
Chile	1
Norway	1
India	1

Table 3
Study Design and Method Used in Data Collection

Study Design	Number of Studies	The Method Used to Collect Data
Quantitative	12	Questionnaire
Qualitative	13	Interviews, focus groups, case studiesdirect observation, document analysis
Mixed method	3	Interviews, focus groups, document analysis, structured/ unstructured questionnaires, and literature review

The included studies were from 13 countries including Australia, Canada, Chile, China, Egypt, India, Israel, Korea, Lebanon, Norway, Sweden, the UK and the USA (See Table 2). These studies were methodologically diverse; 13 were qualitative studies derived from interviews, focus groups, observations, and document analysis; 12 were quantitative studies using questionnaires; and three were mixed methods studies (see Table 3). Most of the studies were found in the healthcare sector (n=20,) followed by business organizations (n=7), education (n=3), and public service (n=2) organizations. The studies included a broad spectrum of participants: nurses, doctors, managers, administrators, students, teachers, community-level officials, and non-government agencies.

Quality Appraisal

Overall, the studies included were of high quality. Out of 28 peer-reviewed papers appraised, 19 had a quality score equal to or > 75%. The quality score of qualitative studies was the highest, followed by quantitative and mixed studies (see Table 4).

Table 4
Study Design and Methodological Scores

Study design	Number of studies and methodological appraisal score				
	20 % (*)	40%	60 % (**)	80 % (***)	100 % (****)
Quantitative	1		3	3	5
Mixed methods			1		2
Qualitative		3	1	3	6

Table 5
Quality Appraisal of Grey Literature (AACODS)

No Studies Grey literature	Accuracy	Authority	Coverage	Objectivity	Date	Significance
N=4	✓	✓	✓	✓	✓	✓
N=2		✓	✓		✓	
N=44		✓			✓	

Table 6
Themes and Sub-Themes of Dimensions of Data-Driven Culture

Themes (Dimensions of data-driven culture)	Sub-themes
Data-Driven Mindset	Data-driven values Curiosity to explore data Critical thinking Analytical thinking Open-mindedness to overcome resistance to change Accountability of using data responsibly by employees and leaders Flexibility to adapt Agility in leveraging data for swift decision-making Seeking continuous quality improvement
Data-Driven Leadership	Mentorship Data champions Developing and executing of data strategy Data-centric decision making Workforce development Enhancing Employees' commitment and engagement
Data literacy	Knowledge of data sources Ability to access data Data interpretation Data competency Learning from experience Confidence in using data
Data Accessibility	Empowerment Open communication Collaboration Trust in using data
Data Governance	Ensuring data quality Data security Data policies and standards Transparency Data Integration Application of Tools

Themes Emerged

Five themes emerged that characterize the dimensions of data-driven culture; 1. Data-driven mindset, 2. Data-driven leadership, 3. Data literacy, 4. Data accessibility, and 5. Data governance.

Data-Driven Mindset

Cultivating and nurturing a data-driven culture is a long and complex journey that requires a data-driven mindset where people value and use data as a standard way of doing business and understand their role as data producers. The data-driven mindset seems to be the critical factor in organizational culture transformation. People understand their role as data producers and users to synthesize and apply data from different data sources for making data-driven decisions. People having data-driven mindset also focus on critical thinking, open-mindedness, curiosity, openness, innovation, flexibility, agility, continuous learning and problem-solving (French et al., 2009; Kitsios & Kapetaneas, 2022; Medeiros & Maçada, 2022; Pittman et al., 2019). The data-driven mindset also emphasizes understanding the impact of data on organizational performance. Companies have a data-driven culture based on certain values such as accountability, transparency, empowerment and willingness to share information (Kim et al., 2018). Similarly, leaders and managers having a data-driven mindset are also aware of the significance of data in informing their decisions and actions (Soltanifar & Smailhodžić, 2021).

Data-Driven Leadership

Another important dimension of data-driven culture is the data-driven leadership that brings a substantial shift in organizational culture by formulating and reinforcing the data-driven values, vision

and strategy that involves the collection, analysis, and interpretation of data to achieve strategic goals. Data-driven leaders through their actions and behaviours (lead by example) foster a data-driven culture by prioritizing data-driven decision-making, holding employees accountable for the quality and compliance of the data, and promoting data responsibility and transparency to foster a data-driven culture. Moreover, leaders at all organizational levels promote positive attitudes and readiness for the implementation of evidence-based decision-making (Hauck et al., 2013; Melnyk et al., 2021).

Organizational leaders should have a strong disposition toward data usage and encourage data-driven decision-making through empowering, engaging, and transforming their employees into data users. Chen (2020) found that leaders should conceptualize data-driven decision-making culture from three perspectives: collective understanding and acceptance of data-driven decision-making, an institutional conversation and endorsement regarding the sustainability of data-driven decision-making, and an understanding of data-driven decision-making. Organizations require consistent education and reinforcement across all business functions to cultivate data culture. Leaders ensure that policies and procedures are supportive of data-driven decision-making. Leaders work to optimize the data-driven culture by motivating and inspiring people through their examples and the use of success stories to demonstrate sound practices. Leaders drive and monitor data-driven decision-making and invest in competence development for training and educating data literacy among their employees.

Data Literacy

Data literacy includes declarative (knowing what), schematic (knowing why), and procedural (knowing how) knowledge necessary for using data effectively (Chen, 2020). It also includes the skills and capabilities to find, evaluate, synthesize, and communicate information. Data culture occurs when business organizations value, recognize, encourage, and incentivize data literacy within the organization. Further, data literacy is a significant component of "digital dexterity", which means that people with data-driven capabilities understand how to collect and interpret data using technology and turn data into useful insights for achieving better business outcomes. Data literacy is expected to be a part of 80% of organizational strategies and change management programs. Additionally, data literacy operationalizing across the organization will facilitate it in leveraging high-quality data useful for predicting Return on Investment. Moreover, data literacy is also related to the individual capacity to identify relevant business problems, review and identify relevant information for a specific problem, and interpret and suggest corresponding actions to address the given problem.

Data Accessibility

Data accessibility promotes employees' empowerment and autonomy to use data and provides them with the right tools and skillset to make the best use of data for achieving organizational objectives (Jun et al., 2020; Kitsios & Kapetaneas, 2022). Data accessibility means that employees can access the organization's data and feel empowered to use and act on data. Access to data of good quality (Heinrich et al., 2018) is mandatory for data-driven decisions. The absence of accessibility to quality data can deteriorate business insights. Moreover, organizations need to build data ownership across all levels of the organization, providing quality data to end users, building trust in using data, improving transparency and accountability in data use, and encouraging cross-departmental communication and collaboration (French et., 2009). Data accessibility also encourages faster data-driven decision-making, better customer experience, and enhanced operational efficiencies by providing high-quality data access to employees.

Data Governance

Data governance is defined as the processes, policies, standards, and technology required to manage and ensure the availability, accessibility, quality, consistency, audibility, and data security in organizations. A robust data governance foundation allows organizations to develop a strong data culture. Data governance signifies the use of interoperable systems that ensure access to consistent, relevant, and high-quality data throughout the organization. A case study conducted in Tanzania and Zambia reported that increased and improved investment in data systems and data use strengthens the ability of the healthcare sector to make evidence-based decisions to achieve sustainable development goals. Well-integrated data architecture and consistent data management are required for making informed healthcare decisions

for improving the health system. Furthermore, data standards and interoperability focus on the ability to extract data from different sources and transform it into actionable information to make data-driven decisions. Data ethics guidelines such as privacy, confidentiality, inclusiveness, accountability, and trust are also important to determine the fairness of outcomes of data-driven decisions.

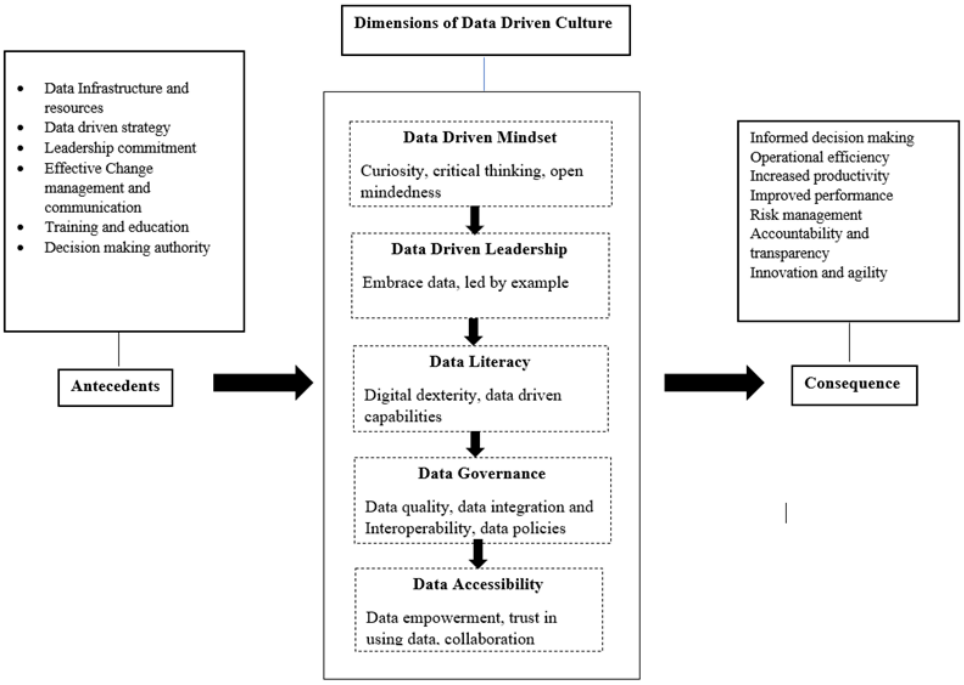

Fig. 2. Dimensions of a data-driven culture

To develop a clear understanding of the given conceptual framework, it is necessary to differentiate the antecedents and dimensions of a data-driven culture. Antecedents are the enablers that facilitate the adoption of data-driven culture while dimensions are the building blocks and attributes that define the culture. In our study, we identified the following antecedents from the existing literature; data infrastructure, data-driven strategy, leadership commitment, change management and decision-making authority. To have a robust data-driven culture, organizations need effective data infrastructure and technological framework to manage and leverage data (Mikalef et al., 2019; Westerman et al., 2014). Another important factor that facilitates the adoption of a data-driven culture is the data-driven strategy that ensures the alignment of organizational goals with timely and relevant data (Sylvestre, 2024).

Organizations having data-driven strategies incorporate data-driven decision-making at all levels of organization. Leadership commitment is another factor that fosters a data-driven culture. It was found that leaders who exemplify the use of data and invest in data-driven initiatives create a top-down influence to motivate employees to embrace data (Brynjolfsson & McElheran, 2016; Marsh & Farrell, 2015; Wayman et al., 2017). Coupled with a data-driven strategy, employee training and education in data analytics have a strong impact on driving data-informed decisions (Ajegbile et al., 2024; Conejero et al., 2021; Mandinach, 2012). Organizations that have effective management practices provide positive support and commitment (Hora et al., 2017; Mitra et al., 2019). It creates a sense of urgency for the desired change in the organization. Moreover, the delegation of decision-making authority is critical for empowering employees to access data for more informed decisions (Brynjolfsson & McElheran, 2016).

Statement of Principles Finding

The relationship between multiple dimensions is interdependent where each dimension strengthens the others. A data-driven mindset is a fundamental dimension that encourages people at all organizational levels to seek relevant data and evidence to support their decisions. Employees with a data-driven mindset are naturally inquisitive and proactively seek data to explore trends, patterns, and insights that can lead to better business outcomes. The relationship between a data-driven mindset and data-driven leadership is interconnected. When leaders and employees share a data-driven mindset, there is alignment in their

values and vision, leading to a cohesive approach to leveraging data to achieve organizational goals.

Data-driven leaders also recognize the importance of data literacy in their workforce. They actively invest in training and educational initiatives to improve the data skills of employees. By promoting data literacy, leaders enable their teams to understand and interpret data effectively, fostering a data-driven mindset throughout the organization. When employees have the necessary data literacy, they feel more empowered to engage with data, analyse it, and use it to inform their decision-making. Data literacy is also crucial for understanding and adhering to data governance policies. When employees are data-literate, they are better equipped to handle data responsibly by following established governance principles. Data governance initiatives play a crucial role in facilitating data accessibility. Clear guidelines and policies for data access and usage empower employees to use them confidently, knowing that they adhere to established standards.

Strengths and Limitations

This review incorporates peer-reviewed articles from four international databases and grey literature to provide a more comprehensive view of the data-driven culture. Further, this review included all types of study designs, including qualitative, quantitative, and mixed-methods studies and applied two methodological appraisal tools, using MMAT for peer-reviewed literature and the ACCODS list for grey literature. We may have included other databases and search engines to look for more relevant literature but restricted our searches due to time shortage. Moreover, our searches were restricted to English, and we may have missed important literature in other languages. Another limitation of our study is the underrepresentation of other sectors such as manufacturing, government and nonprofit organizations that could affect the generalizability of our study. The inclusion of these sectors increases the comprehensiveness of our findings as data-driven approaches are pivotal in formulating public policy (Hume & West, 2020; Matheus et al., 2020). Future studies can also highlight strategies for nurturing DDC in industrial settings that differ significantly from service sectors like healthcare and education (Brynjolfsson & McElheran, 2016).

Interpreting the Findings in the Context of Wider Published Literature

The insights gained from analysing literature are useful for extending the body of knowledge relating to the multi-dimensional nature of data-driven culture. Focusing on the multi-dimensional nature of data-driven culture is crucial as it acknowledges the interconnectedness and complexity of various aspects of data-driven culture for ensuring a holistic and integrated approach involved in leveraging data for organizational success. A multi-dimensional approach includes not only the technological aspect but also individual and organizational dimensions for navigating the complexities of today's business landscape and staying competitive in the business world. It also reflects the interplay of various dimensions to strengthen the data use culture. For instance, awareness of the need to use high-quality data to inform decisions, access to complete and reliable data, motivation to use data through data use champions, and empowerment to act on the data they have access to, work in tandem to stimulate the data use culture.

The data-driven mindset, values, norms, and assumptions at both leaders' and followers' levels have a strong impact on creating a data-driven culture. Melnyk et al., (2017) proposed a robust culture of inquiry and critical thinking as a precursor to the routine use of evidence. These cultural characteristics in organizations drive the individual to ask questions to better understand the problem and thus acquire the best available evidence for decision-making (Melnyk et al., 2017). Our findings are further supported by the study conducted in the school setting where leaders played a pivotal role in fostering a data-driven culture by understanding the value of data (Park & Datnow, 2009). It also includes capacity building and professional development among the teachers in the use of data tools and data analysis. Scholars have documented that leaders' values and dispositions toward data influence employees' behaviour toward the usage of data (Marsh & Farrell, 2015).

Possessing ownership of quality data sets is required to break data siloes and to ensure data-driven decision-making within the organizations. A case study conducted on Airbnb supports the relationship between data accessibility and culture. As the leading online lodging platform, Airbnb fosters data exploration and accessibility by using various interventions like data portals and data universities to empower employees with the right data skill set. Another case study conducted on Netflix also suggested

that a significant amount of autonomy and instant access to data is the key to making data-informed decisions. Data governance is required to manage data as a key strategic asset and specify data policies, procedures, standards, and decision rights for maximizing the value of data assets in organizations (Abraham et al., 2019). Data governance mechanisms are also used to overcome inaccurate and inconsistent data that obstruct informed decisions (Kim & Cho, 2018).

Future Directions

This systematic review serves as a guide for future studies by offering a clear and replicable framework. Acknowledging the underrepresented sectors can help future researchers to explore in depth the effectiveness of data-driven practices. Furthermore, the inclusion of grey literature reduces the publication bias and encourages future researchers to adopt a similar inclusive approach. Adopting a data-driven mindset is conducive to fostering a data-driven culture (French et al., 2009; Jun et al., 2020). Leaders set the vision and strategic goals of the organizations that reflect the clear purpose and significance of data usage. Further research is needed to explore the challenges and opportunities to inculcate data-driven values in organizations.

Harland et al., (2022) found that to fully embrace the concept of data accessibility, the organizational culture should encourage information sharing. It is important to understand how data can be utilized to make well-informed decisions, extract relevant data, which skills are necessary for data analysis, and how to best apply data for making sound decisions. This is because there is a risk that leaders, managers, or policymakers can make poor decisions due to a lack of reliable data. Future research should investigate ways of data governance mechanisms to help organizations maintain a standardized and trustworthy data exchange environment. This systematic review identified the multiple dimensions which are applicable across various industries. These dimensions were validated through existing literature and expert feedback. However, implementation of these dimensions varies according to regulatory requirements, data maturity, infrastructure and size of the organization. Regulatory requirements ensure data compliance, accountability and transparency of handling and using data. The regulatory requirement has a direct impact on company data governance structure such as GDPR compliance for ensuring patients' privacy. Similarly, well-defined industry norms have a strong impact on the companies to foster DDC to stay competitive (Economou et al., 2023). Moreover, technological advancements such as Big Data and AI have a strong influence on data accessibility, and analytical capabilities to make informed decisions.

CONCLUSION

This systematic review integrated previously fragmented and disconnected research findings on data-driven culture. The data-driven culture comprises five dimensions, namely, data-driven mindset, data-driven leadership, data literacy, data accessibility, and data governance, that are essential for making informed decisions. Thus, business organizations must adhere to these dimensions in transforming themselves into data-driven organizations and aligning their business and data strategies to become innovative and competitive. Moreover, this review produced a data-driven culture framework with multiple dimensions interrelated. This framework can be applied to various contexts; however, the framework may provide dissimilar results in different settings.

Practical Implications

This review will help practitioners (e.g. leaders and managers) working across different fields such as manufacturing and healthcare to understand that transforming an organizational culture into data-driven requires a holistic approach at three levels: people, process, and technology. For instance, leaders should develop interventions to induce a data-driven culture in their organizations. Leaders should appoint change agents who provide regular backing to the cultural transformation initiatives. They should work on treating data as a key strategic asset, giving data access to authorized individuals, building up data literacy, through training of employees to equip them with a wide range of data analysis skills, and adhering to standardized data governance practices. Additionally, they should also focus on data maturity that reflects the development of the organization's data-related capabilities, processes, and practices. Data maturity provides the necessary infrastructure and practices to enable the data-driven culture to thrive. Further research on the multiple dimensions of data-driven culture can help identify

causal relationships between specific practices and outcomes. For example, it can establish whether a strong data-driven mindset leads to improved data literacy or if data governance is a key driver of data accessibility. We also identified that there was a lack of studies that addressed the data-driven culture systematically at the nano level (individual mindset and values) and meso level such as organizational level and data governance.

Competing Interests

The authors declared no competing interests.

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