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Article

Identifying and Prioritizing Factors for Effective Data-Driven Decision-Making in Organizations: A DEMATEL Approach

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Abstract

The increasing volume of data necessitates its effective transformation into managerial decisions for organizational performance and sustainability within Business Process Management. However, challenges like poor data quality, technological deficiencies, cultural resistance, and skill gaps often hinder this crucial process; thus, a profound understanding of the causal relationships among influencing factors is essential to address these impediments. This study utilizes the Decision-Making Trial and Evaluation Laboratory method, a robust structural and multi-criteria analysis technique, to analyze complex causal interdependencies. DEMATEL quantifies expert judgments and maps cause-and-effect relationships, offering a systemic perspective distinct from other Multi-Attribute Decision-Making methods. We examine five key factors: data quality, data infrastructure & technology, data culture & governance, data analytics literacy, and business-strategy alignment. Expert data from five management-level professionals were used to construct direct and total-relation matrices, deriving influence and causality scores. The DEMATEL application will provide comprehensive factor interdependencies via direct and total-relation matrices. $D - R$ indicators will classify cause and effect factors, culminating in a causal map illustrating the system's structure and each factor's role. This study aims to offer a structured framework for effective data-driven culture and business process optimization.

Keywords: data-driven organizations; decision-making; DEMATEL method; data quality; data infrastructure; data culture; data analytics literacy; business-strategy alignment; causal relationships; business process management

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1. Introduction

In the contemporary economic and technological landscape, which is characterised by an exponential increase in the volume, velocity and variety of data (Big Data), the ability of organisations to efficiently leverage these information resources has become a key factor in performance and sustainability. Transforming raw data into actionable insights and subsequently into well-founded managerial decisions is a strategic imperative that confers a distinctive competitive advantage in a volatile and dynamic business landscape. Within the Business Process Management (BPM) disciplinary framework, the judicious integration of data into decision-making processes is a systemic necessity for optimising operational procedures, stimulating innovation and ensuring organisational adaptability.

However, the process of transitioning from data collection to making strategic decisions based on empirical evidence is often fraught with complex, multidimensional challenges. Academic

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literature and managerial practice highlight significant obstacles, such as suboptimal data quality, technological infrastructure deficiencies [1], cultural resistance to change, information fragmentation [2], and gaps in digital and analytical literacy among staff [3]. These systemic impediments can substantially diminish the return on investment in advanced data analytics solutions, creating a critical gap between an organisation's aspiration to be 'data-driven' and its actual operational reality.

In order to address these dysfunctions holistically and optimise the process of transforming data into decisions, it is essential to have a profound understanding of the causal and interdependent relationships among the critical factors influencing this endeavour. Traditional analytical methods often struggle to model the complexity of nonlinear interactions and reciprocal influences among multiple variables. In this context, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is a robust tool capable of overcoming these limitations. DEMATEL not only identifies critical factors, but also precisely maps cause-and-effect relationships, offering a systemic and nuanced perspective on the dynamics of reciprocal influences. DEMATEL is chosen because it can quantify experts' qualitative judgements, transforming them into structured information that clarifies which factors have the most significant causal influence (cause factors) and which factors are most strongly influenced (effect factors). This differentiation is crucial for the strategic prioritisation of managerial interventions and the efficient allocation of resources.

DEMATEL is chosen for this research due to its unique capability to quantify experts' qualitative judgements, transforming them into structured information that clarifies which factors have the most significant causal influence (cause factors) and which factors are most strongly influenced (effect factors). This differentiation is crucial for the strategic prioritisation of managerial interventions and the efficient allocation of resources.

Unlike other Multi-Attribute Decision-Making (MADM) methods that often focus on selecting an optimal option or identifying a single critical factor, DEMATEL provides a comprehensive matrix framework for analyzing causal relationships and interdependencies between various factors. This allows for a more holistic and dynamic approach, which is particularly beneficial in complex domains like data management where factors are highly interconnected and variable. An additional advantage of DEMATEL is its ability to facilitate the indirect improvement of critical factors when direct influence is not feasible, by strengthening their determinants to achieve systemic enhancement. This makes DEMATEL a valuable strategic management tool, as it offers an intuitive understanding of system dynamics and enables the differentiation of cause and effect factors for strategic prioritization of interventions. Furthermore, it quantifies influence intensity, providing a comprehensive view of both direct and indirect reciprocal impacts among factors.

The primary aim of this study is to identify, analyse and prioritise the causal relationships between the key factors that influence the success of the process of transforming data into managerial decisions in data-driven organisations. This study is particularly useful for organizations seeking to enhance their data-driven culture and optimize business processes, ultimately contributing to their long-term sustainability by ensuring more informed and effective decision-making. By applying the DEMATEL method, this study aims to provide a structured decision-making framework and contribute to the development of effective strategies for adopting a data-driven culture and optimising business processes.

This paper is structured as follows: section 2, "Materials and Methods," provides a detailed explanation of the DEMATEL methodology, outlining its fundamental steps and the advantages that justify its selection for this research. Section 3, "Results," presents the empirical findings obtained from the application of the DEMATEL method, including the direct-relation matrix, total-relation matrix, and the assessment of factor influence and causality. Section 4, "Discussion," interprets these results in the context of previous studies and discusses their implications for organizations striving to become data-driven. Finally, section 5, "Conclusions," summarizes the main contributions of this study and suggests avenues for future research.

2. Theoretical Framework

The effective transformation of raw data into actionable managerial insights is contingent upon a constellation of interrelated organizational, technological, and human factors. This section delineates the principal constructs examined in this study, each substantiated by contemporary scholarly literature, to elucidate their individual and synergistic contributions to data-driven decision-making efficacy. By critically reviewing the dimensions of Data Quality (DQ), Data Infrastructure and Technology (DIT), Data Culture and Governance (DCG), Data Analytics Literacy (DAL), and Business-Strategy Alignment (BSA), this section establishes a conceptual foundation for understanding how organizations can systematically leverage data assets to enhance strategic and operational performance in increasingly complex and dynamic environments. Table 1 presents the factors included in the analysis.

Table 1. Factors included in the DEMATEL analysis.

Factor	Factor	References
A	Data Quality (DQ)	[4–10]
B	Data Infrastructure & Technology (DIT)	[6–8,11–14]
C	Data Culture & Governance (DCG)	[5–7,15,16]
D	Data Analytics Literacy (DAL)	[6,7,11,15]
E	Business-Strategy Alignment (BSA)	[5,7,16,17]

DQ refers to the degree to which data are fit for their intended use in operations, decision-making, and strategic planning. It is generally operationalized through dimensions such as accuracy (truthfulness), completeness (extent of missing data), consistency (absence of contradictions), timeliness (currency), and validity (adherence to defined formats and rules). Inadequate data quality compromises the integrity of analytical processes, introduces cognitive and computational biases, and may result in decisions based on erroneous assumptions or misleading trends.

From a systems theory perspective, data quality represents an upstream determinant in the information value chain: errors introduced at the point of data capture or during preprocessing can propagate through successive stages of analysis and modeling, magnifying their detrimental effects. Moreover, high-quality data underpin organizational trust in analytics, thereby influencing user adoption, decision confidence, and overall return on data investments. Consequently, data quality is not merely a technical attribute but a strategic asset integral to sustaining competitive advantage in information-rich contexts.

DIT encompasses the technical systems, platforms, and tools that support the entire data lifecycle—from ingestion and storage to processing, analysis, and dissemination. Core components include databases, data lakes, cloud-based architectures, ETL (extract-transform-load) pipelines, APIs, analytics platforms, and real-time processing engines. The efficiency, scalability, and interoperability of this infrastructure determine an organization's capacity to respond to data velocity, volume, and variety—key attributes of the so-called "Big Data" paradigm.

In a dynamic business environment characterized by rapid technological evolution and increasing data complexity, a resilient and adaptable DIT enables not only efficient data handling but also accelerates innovation and supports predictive, prescriptive, and automated decision-making. A robust data infrastructure also facilitates integration across heterogeneous sources, enabling more comprehensive and context-rich analyses. Organizations that lack adequate technological frameworks risk delayed insights, fragmented knowledge bases, and systemic inefficiencies, thereby reducing the strategic utility of their data assets.

DCG refers to the set of organizational norms, values, policies, and institutional mechanisms that regulate how data are perceived, managed, and utilized. A strong data culture is characterized by normative support for evidence-based decision-making, cross-functional collaboration around data, and widespread data literacy. It reflects an organizational mindset in which data are regarded as a critical resource and a driver of continuous improvement.

Complementarily, data governance involves the formalization of processes and responsibilities that ensure data quality, security, privacy, accessibility, and compliance with regulatory standards. Effective governance structures delineate ownership, stewardship, and accountability across the data lifecycle. From an institutional theory perspective, governance mechanisms legitimize data practices, mitigate risks, and institutionalize ethical and lawful data usage. Without a coherent culture and governance framework, organizations may experience informational asymmetries, resistance to change, fragmentation of datasets, and reduced alignment between analytical outputs and managerial needs. Therefore, DCG is fundamental not only for ensuring ethical and efficient data use but also for embedding analytics within organizational routines and decision architectures.

DAL denotes the cognitive and technical competencies that enable individuals within an organization to understand, interpret, critique, and apply data and analytical results. This construct encompasses a spectrum of skills, including numeracy, statistical reasoning, data visualization, tool proficiency, and contextual interpretation of findings. DAL is a human capital asset that conditions the extent to which analytical insights are effectively integrated into decision-making processes.

Organizations with high DAL levels tend to experience better cross-functional communication, reduced dependence on data specialists for routine tasks, and greater agility in responding to analytical findings. Conversely, deficits in analytics literacy create interpretive bottlenecks, reduce trust in insights, and can lead to misapplication of results. From the perspective of organizational learning theory, DAL represents a key capability for absorptive capacity—that is, the ability to recognize, assimilate, and apply new knowledge. In increasingly automated and AI-augmented environments, developing advanced DAL across hierarchical levels ensures that technological potential is matched by interpretive competence, thereby maximizing the value extracted from data systems.

BSA refers to the degree of congruence between an organization's data-driven initiatives and its overarching strategic objectives, priorities, and performance metrics. This alignment ensures that data efforts are purposefully directed toward solving core business problems, enhancing value creation, and enabling strategic differentiation. BSA acts as a contextual anchor, connecting analytical projects with desired business outcomes.

Strategic misalignment, by contrast, leads to analytics initiatives that are disconnected from operational realities, resulting in wasted resources, unutilized insights, and diminished organizational impact. From a strategic management perspective, BSA is essential for ensuring that analytics serve as a source of sustainable competitive advantage rather than a cost center. It involves the integration of analytics within strategic planning processes, KPI formulation, and performance monitoring systems. Organizations that embed data practices within their strategic frameworks can more effectively optimize processes, identify emergent opportunities, and adapt to environmental volatility, thereby enhancing organizational resilience and innovation capacity

Together, the five constructs presented—DQ, DIT, DCG, DAL, and BSA—form an integrated framework that captures the multifaceted nature of data-driven decision-making. These dimensions interact dynamically, with deficiencies in one area often undermining progress in others. Understanding their interdependencies and contextual relevance enables organizations to design more coherent, adaptive, and performance-oriented data strategies. In the following sections, this conceptual model will guide the empirical analysis of how organizations operationalize data capabilities to achieve sustained strategic and operational excellence.

3. Materials and Methods

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is a structural and multi-criteria analysis technique founded on the theory of directed graphs (digraphs). This method is designed to analyze the complex causal and interdependent relationships among a set of factors or criteria, being particularly pertinent for studying complex systems where reciprocal interactions are prevalent. DEMATEL enables not only the identification of critical system elements but also the

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visualization of their causal structure, differentiating between factors that exert a predominant influence and those that are primarily influenced.

The methodological advantages of DEMATEL, which justify its selection for the present research, include visualising the systemic structure and facilitating the construction of a causal map that illustrates direct and indirect relationships between factors. This offers an intuitive understanding of system dynamics. Furthermore, it enables the differentiation of cause and effect factors by classifying them into cause and effect categories, which is essential for the strategic prioritisation of interventions. Another advantage is the ability to quantify influence intensity and measure both direct and indirect influences among factors, providing a comprehensive view of reciprocal impact. Lastly, the method has been shown to be effective in complex decision-making situations, efficiently analysing multi-criteria decision problems with interconnected criteria, which are specific to strategic management, quality management and, in this case, data management.

This qualitative research study is based on the expertise of professionals with relevant experience. Respondents were selected from individuals with management experience in data-driven organisations. The DEMATEL methodology specifically requires 4–5 respondents to assess the interactions between factors [18–20]. The factors were evaluated based on responses from five management-level respondents from organisations with a strong data orientation, each with at least 2 years' experience, in order to assess the degree of mutual influence between the relevant factors. Data were collected in June 2025. The questionnaire was structured as a relationship matrix containing six factors, and participants were asked to rate the influence of each pair of factors (36 arrangements).

The fundamental steps of applying the DEMATEL method are rigorously structured and involve the following operations. First, the set of factors is defined by explicitly delimiting and validating the relevant factors for the research problem, based on a review of specialised literature and preliminary expert consultation. Next, the initial direct-relation matrix A is constructed by collecting expert judgements on the direct influence of each factor on the others. This is performed using a predefined numerical scale. For example:

- 0 = no influence,
- 1 = weak influence,
- 2 = moderate influence,
- 3 = strong influence,
- 4 = very strong influence).

Expert opinions are aggregated statistically to form a consolidated initial matrix. The next step is to normalise the matrix of direct relations Y, by scaling the values of matrix A to ensure compatibility with subsequent calculations.

Normalisation is performed according to the following formula::

$$Y = A \cdot k \tag{1}$$

$$\text{Where: } A = \begin{bmatrix} 0 & a_{12} & \dots & a_{1j} & \dots & a_{1n} \\ a_{21} & 0 & \dots & a_{2j} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ a_{i1} & a_{i2} & \dots & a_{ij} & \dots & a_{in} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nj} & \dots & 0 \end{bmatrix} \tag{2}$$

$$k = \frac{1}{max_{1 \le i \le n}\left(\sum_{j=1}^{n} a_{ij}\right)} \ (i, j = 1, 2, \dots, n) \tag{3}$$

where n is the number of factors and $max_{1 \le i \le n}\left(\sum_{j=1}^{n} a_{ij}\right)$ is the maximum value among the sum of elements in rows and the sum of elements in columns. Then, the total-relation matrix T is calculated, determining the total influences (both direct and indirect) among factors. This matrix is derived from the normalised matrix Y and the identity matrix I (unit matrix), using the relationship:

$$T = Y \cdot (I - A)^{-1} \quad (4)$$

The threshold for assessing the α-factor is established using the following formula:

$$\alpha = \frac{\sum_{i=1}^{n} \sum_{i=1}^{n} [t_{ij}]}{N} \quad (6)$$

where $N = n^2$ denotes the total number of elements or relationships within the influence matrix.

Once the comprehensive influence matrix is computed, two key metrics can be derived for each criterion: the impact score D_i and the causal score R_j (Table 4).

The impact score D_i of a given factor represents the cumulative influence it exerts on all other factors, and is calculated as:

$$D_i = \left[\sum_{j=1}^{n} t_{ij} \right]_{nx1} = [t_i]_{nx1'} \quad (7)$$

for each i ∈ {1,2, … , n}.

Conversely, the **causal score** RjR_jRj reflects the total influence that all other factors exert on a particular factor, and is given by:

$$R_j = \left[\sum_{j=1}^{n} t_{ij} \right]_{1xn} = [t_j]_{nx1'} \quad (8)$$

for each j ∈ {1,2, … , n}.

4. Results

The interdependencies among the identified factors were systematically examined using the Decision-Making Trial and Evaluation Laboratory (DEMATEL) methodology. This approach facilitated the construction of a series of matrices that capture the structure and intensity of mutual influences between the factors. Table 2 displays the direct influence matrix, which quantifies the extent to which each factor directly impacts another. The values within this matrix are derived from expert assessments, where each numerical entry reflects the perceived magnitude of direct influence exerted by one factor upon another, based on structured evaluative input from the study's participants.

Table 2 displays the direct influence matrix. This matrix quantifies the extent to which each factor directly impacts another. The values within this matrix are derived from expert assessments, where each numerical entry reflects the perceived magnitude of direct influence exerted by one factor upon another, based on structured evaluative input from the study's participants. This step corresponds to the construction of the initial direct-relation matrix

Table 2. Direct-relation matrix.

Factor	A	B	C	D	E
A	0	0.045	0.05	0.045	0.045
B	0.054	0	0.05	0.05	0.05
C	0.05	0.054	0	0.045	0.045
D	0.045	0.059	0.059	0	0.041
E	0.05	0.059	0.054	0.05	0

Table 3 presents the Total-relation matrix. This matrix encapsulates the full extent of influence that each factor exerts on and receives from all other factors, accounting for both direct and indirect

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relationships. For example, the values in row 'A' indicate the total influence of Data Quality on all other factors, including indirect effects.

Table 3. Total-relation matrix highlighting (*) factors with significant influence $(\alpha > -0.05)$.

Factor	A	B	C	D	E
A	-0.011*	-0.055	-0.059	-0.054	-0.053
B	-0.064	-0.013	-0.06	-0.059	-0.058
C	-0.059	-0.064	-0.012*	-0.054	-0.054
D	-0.055	-0.069	-0.068	-0.012*	-0.05
E	-0.06	-0.069	-0.065	-0.059	-0.012*

Subsequently, the row and column sums are calculated. For each factor, two key indicators are determined from the total-relation matrix T: the sum of influences given (D), determined by summing the elements of each row in matrix T, which quantifies the total influence a factor exerts on all other factors; and the sum of influences received (R), calculated by summing the elements of each column in matrix T, which indicates the total influence a factor receives from all other factors. Based on the values of D and R, the prominence and relation indicators are determined. The prominence indicator ($D + R$), the sum of D and R, measures the total importance of a factor within the system, indicating its degree of involvement in general interactions. The relation indicator ($D - R$), the difference between D and R, classifies factors into cause and effect categories. A positive D−R value designates a cause factor, while a negative value indicates an effect factor. Finally, the causal map is constructed, which is a graphical representation of the factors in a cartesian coordinate system, with $D + R$ on the horizontal axis and $D - R$ on the vertical axis (Figure 1). This allows for visual inspection of the causal relationships structure and rapid identification of the role of each factor.

Table 3. Assessment of the influence and causality of factors.

Factor	D	R	D+R	D-R	Dominant characteristic
A	-0.233	-0.249	-0.482	0.016	Cause
B	-0.254	-0.270	-0.524	0.016	Cause
C	-0.243	-0.265	-0.508	0.021	Cause
D	-0.254	-0.238	-0.492	-0.016	Effect
E	-0.265	-0.227	-0.492	-0.038	Effect

The current study used the DEMATEL method to identify and prioritise factors for effective, data-driven decision-making within organisations. The analysis revealed that DQ, DIT and DCG are causal factors, while DAL and BSA were identified as effect factors. This suggests that interventions aimed at improving DQ, DIT and DCG are likely to positively influence DAL and BSA, thereby enhancing data-driven decision-making and organisational performance. These findings provide a nuanced understanding of the causal relationships within the complex ecosystem of data-driven decision-making and offer actionable insights for strategic management.

5. Discussion

Comparing these results with relevant literature from the last five years reveals significant convergence and distinct nuances, particularly in the classification of factors as causes or effects. The methodology employed in the example study by Estiri et al. [18], which used DEMATEL-MABAC for High-Performance Work Systems, demonstrates its ability to identify critical interdependencies — a strength mirrored in our current analysis.

Our findings regarding the cause factors (DQ, DIT and DCG) largely align with the prevailing academic discourse, which often emphasises these elements as prerequisites for successful data-driven initiatives.

Classifying data quality as a primary causal factor aligns with extensive literature. For example, Delinschi et al. [4] emphasise that robust data quality assessment methodologies are foundational as well as procedural, and directly impact the reliability and trustworthiness of any data-driven outcome. This is consistent with our finding that poor data quality can compromise the integrity of analytical processes and lead to erroneous decisions. Similarly, Alharasis and Alkhawaldeh [5] demonstrate that the effective implementation of advanced accounting information systems is linked to improvements in accounting data quality. This further supports the idea that DQ is a fundamental driver that influences subsequent stages of data utilisation and decision-making accuracy. Our study reinforces the idea that DQ is not just a desirable attribute, but a critical factor that determines the effectiveness of all other data-related endeavours.

The identification of DIT as a causal factor is well supported by studies focusing on the technological underpinnings of data-driven transformation. Chakraborty et al. [6] discuss the evolution towards data-driven paradigms in critical sectors such as medicine and healthcare. They emphasise that such advancements fundamentally rely on sophisticated and robust technological infrastructures capable of handling vast and complex datasets. Our results indicating DIT's causal role emphasise that resilient, scalable and interoperable infrastructure is determinative of an organisation's capacity to process, store and utilise data effectively, thereby accelerating innovation. This reflects the wider consensus that inadequate DIT can severely hinder an organisation's ability to extract timely insights, leading to systemic inefficiencies.

The finding that DCG acts as a causal factor is consistent with an expanding body of literature that acknowledges the pivotal role of organisational culture and formal governance in successful data strategies. Chaudhuri et al. [6] explore how emerging technologies can foster a data-driven culture and enhance innovation capabilities, implicitly acknowledging that a conducive culture is a prerequisite. Furthermore, in their discussion of digital academic leadership in higher education, Jing et al. [7] highlight that effective data utilisation in such contexts necessitates a strong underlying data culture. Our study confirms that robust DCG, encompassing shared data values and formal management policies, provides the normative framework necessary for evidence-based decision-making. It also formalises processes for data quality, security and compliance, aligning with the view that DCG is fundamental to truly embedding analytics into an organisation's routine operations and strategic thinking.

While the 'cause' factors demonstrate a high degree of alignment, classifying DAL and BSA as 'effect' factors provides a more nuanced perspective, departing from the way in which some recent literature often implicitly or explicitly positions these elements as primary drivers or preconditions.

Many studies emphasise the importance of data literacy for individuals and organisations to leverage data effectively. For example, Koltay [11] describes the evolution from data literacy to AI literacy, highlighting their growing importance, while Taş [15] emphasises the pivotal role of data literacy in university-industry collaborations. However, our DEMATEL analysis provides a different perspective: it suggests that DAL is an outcome significantly influenced by robust cause factors. Unlike studies that treat data literacy as an isolated skill, our findings suggest that DAL is fostered and facilitated by preconditions such as a strong data culture, reliable data quality and accessible infrastructure. This implies that providing training alone may be ineffective if the underlying data environment (DQ, DIT, DCG) is not conducive. Employees' ability to interpret and utilise data effectively (DAL) appears to be a consequence of, or an emergent property of, a well-established data foundation. This offers valuable insight for managerial interventions: rather than simply promoting literacy initiatives, organisations should first ensure that the foundational elements are in place.

In the literature on strategic management and data governance, BSA is often presented as an important precondition for the success of data-driven initiatives, ensuring that data efforts are directed towards achieving strategic objectives. However, this study's classification of BSA as an

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effect factor provides an alternative perspective. While many authors implicitly or explicitly advocate initial alignment, our DEMATEL results suggest that effective alignment may result from well-functioning core data components. If an organisation struggles with data quality (DQ), lacks adequate infrastructure (DIT) or has a weak data culture (DCG), aligning data initiatives with broader business strategies becomes inherently challenging, regardless of initial strategic intent. This implies that congruence between data efforts and strategic objectives improves naturally as foundational 'cause' factors are strengthened. Therefore, in this model, BSA is a dependent outcome, achieved when the underlying data ecosystem (DQ, DIT and DCG) is mature and robust enough to genuinely support and contribute to strategic goals.

In conclusion, while the current study confirms the universally acknowledged significance of data quality, infrastructure and culture in data-driven decision-making, its application of the DEMATEL method provides a unique causal understanding. Identifying Data Analytics Literacy and Business-Strategy Alignment as effect factors suggests that efforts to improve these areas may be more fruitful when preceded by robust advancements in DQ, DIT, and DCG. This offers a structured framework for prioritising managerial interventions, suggesting a sequential approach to fostering an effective, data-driven culture and optimising business processes for long-term sustainability and enhanced decision-making capabilities.

6. Conclusions

This This study employed the DEMATEL method to identify and prioritise the key factors necessary for effective, data-driven decision-making within organisations. The analysis revealed that DQ, DIT and DCG are causal factors. In contrast, DAL and (BSA were identified as effect factors.

These results suggest that improving DQ, DIT and DCG is likely to positively influence DAL and BSA, thereby improving data-driven decision-making and organisational performance. The study provides a nuanced understanding of the causal relationships within the complex ecosystem of data-driven decision-making, offering actionable insights for strategic management.

Compared to recent literature, classifying DQ, DIT and DCG as causal factors is consistent with the prevailing academic discourse, which considers them prerequisites for successful data-driven initiatives. For instance, reliable data is essential for accurate data-driven outcomes, and implementing advanced accounting information systems improves accounting data quality. Furthermore, DIT is a causal factor supported by studies focusing on the technological foundations of data-driven transformation, which emphasise that robust infrastructures are essential for managing large, complex datasets. DCG as a causal factor is also consistent with literature recognising the essential role of organisational culture and formal governance in successful data strategies.

Classifying DAL and BSA as effect factors provides a more nuanced perspective. While many studies emphasise the importance of data literacy, the DEMATEL analysis in this study indicates that DAL is significantly influenced by robust causal factors. This implies that training efforts may be ineffective if the underlying data environment is not favourable. Employees' ability to interpret and use data effectively (DAL) appears to be a consequence of a well-established data foundation. Similarly, while BSA is often presented as a prerequisite for the success of data-driven initiatives, DEMATEL results suggest that effective alignment can be achieved through the proper functioning of data building blocks. Congruence between data-related efforts and strategic objectives improves as fundamental causal factors are strengthened.

In conclusion, this study suggests that efforts to improve DAL and BSA may be more effective if preceded by solid progress in DQ, DIT and DCG. This provides a structured framework for prioritising managerial interventions and suggests a sequential approach to cultivating an effective, data-driven culture, as well as optimising business processes for long-term sustainability and improved decision-making capabilities.

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