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Bibliometric Mapping of Knowledge and Research Agenda on Data and Analytics in the field of Business Strategy and Information Systems Management

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BIBLIOMETRIC MAPPING OF KNOWLEDGE AND RESEARCH AGENDA ON DATA AND ANALYTICS IN THE FIELD OF BUSINESS STRATEGY AND INFORMATION SYSTEMS MANAGEMENT

Introduction

With the proliferation of digital and data-driven technologies such as Big Data (BD), Data and Analytics (D&A), and Artificial Intelligence (AI), data management has become even more crucial for the strategic direction of business. Yet many organizations still struggle to integrate data as a core component of their information systems and business strategies (Baecker, Weking, Hein, & Krcmar, 2025; Medeiros & Maçada, 2022; Reddy, Bhattacharjee, Mishra, & Mandal, 2022; Shah, 2022). To generate value from data, several organizational factors are regarded as critical challenges: data literacy (Cezar & Maçada, 2021), mindset and cultural change, data governance mechanisms, and varied data strategies for sharing, protecting, and monetizing data (Medeiros, Hoppen, & Maçada, 2020; Maia, Maçada, & Lunardi, 2025; Quach *et al*., 2022), as well as the development of business capabilities (Bisswang, Petrik, Richter, & Zimmermann, 2025).

In the scientific literature at the intersection of business strategy and information systems management, the debate agenda on underlying issues of D&A management and capabilities is also emerging and expanding. Over the past ten years, publications on the topic have increased substantially, especially in the last five years. It is worth noting that the tragic event of the COVID19 pandemic accelerated the pace of digitalization (Reddy *et al*., 2022; Shah, 2022), fueling the debate on data-driven management and business strategy.

Between 2015 and 2019, studies examined how BD is reshaping strategic context (Constantiou & Kallinikos, 2015); the effect of strategic alignment on the relationship between analytic capability and performance (Akter *et al*., 2016); how BD augments resources and shapes new industries (Mazzei & Noble, 2017); the role of data in organizational strategy formulation (Gnizy, 2018); analytic strategy as a component of the "BDA business value framework" (Côrte-Real, Ruivo, Oliveira, & Popovič, 2019); how business analytics relates to strategic processes (Kunc & O'Brien, 2019); and the steps required to implement BD strategies (Tabesh, Mousavidin, & Hasani, 2019).

From 2020 to 2021, research investigated how performance gains from BD depend on chosen business strategy (Suoniemi *et al*., 2020); the impact of data strategy on competitive advantage (Medeiros, Maçada, & Freitas, 2020); data democratization within data strategy (Awasthi & George, 2020); defining data strategy in the digital context (Bhargava *et al*., 2020); a proposed model for data -strategy implementation highlighting organizational and environmental factors (Sun, Hall, & Cegielski, 2020); the relationship among data literacy, data overload, technostress, and their effects on individual performance (Cezar & Maçada, 2021); a systematic literature review on BD strategy suggesting future research assess organizational factors (Walter, Valente, Polónia, & Au-Yongoliveira, 2021); aspects of business intelligence & analytics strategies used to improve performance (Ahmad & Akbar, 2021); inertial forces in Big Data Analytics (BDA) implementation projects and a framework for strategic transformation (Mikalef, Wetering, & Krogstie, 2021); and a theorization of the relationship among data strategy, data governance, data-driven culture, and data science in achieving competitive advantage (Medeiros, Maçada, & Freitas, 2021).

More recently, from 2022 to 2025, conceptual studies have theorized how BDA can secure sustainable competitive advantage (Shah, 2022); typologies of data strategies related to monetization, sharing, and privacy (Quach *et al*., 2022); facilitators and barriers affecting data science strategy formulation and implementation (Reddy *et al*., 2022); multidimensional data-driven culture (mindset, leadership, data literacy, data accessibility, and data governance) and

its influence on decision-making practices (Javed & Akhlaq, 2024); the mediating effect of data literacy on the relationship between data governance and data-driven culture (Fattah, 2024); orchestrated data ecosystems (Salerno & Maçada, 2025a); different forms of social media data monetization (Maia *et al*., 2025); and the mapping of 34 business capabilities (processes, functions, resources, and information) required for data value creation (Bisswang *et al*., 2025).

Empirical studies from 2022 to 2025 have also shown: how data-driven culture and business analytics capabilities affect competitive advantage, considering BD visualization and organizational agility (Medeiros & Maçada, 2022); the relationships among cognitive overload, anxiety, cognitive fatigue, avoidance behavior, and data literacy in big-data environments (Cezar & Maçada, 2023); the impact of BDA on organizational learning, frugal innovation, and competitive agility (Al-Omoush, Garcia-Monleon, & Iglesias, 2024); that business analytics moderates and explicates the relationship between business strategies and competitive advantage (Bhisikar, 2024); that effective data governance improves data quality and fosters a data-driven culture (Salerno & Maçada, 2025b); the relationship between managerial BDA capabilities and organizational agility, with data-driven learning as a mediator (Zhang, Wang, & Wang, 2025); the importance of fostering a positive data oriented mindset to engage individuals in data-driven transformation (Huynh, Veglio, & Gunkel, 2025); and a data strategy- taxonomy outlining key characteristics of data-based strategy formulation (Baecker *et al*., 2025).

Despite the considerable growth in studies on the topic, the role of organizational factors in creating and sustaining value through data has received little attention in existing literature (Aboelmaged & Mouakket, 2020; Fiorini *et al*., 2018; Grover, Chiang, Liang, & Zhang, 2018; Günther, Mehrizi, Huysman, & Feldberg, 2017; Jiwat & Zhang, 2022; Mikalef *et al*., 2021; Reddy *et al*., 2022; Shah, 2022; Suoniemi *et al*., 2020; Wamba *et al*., 2017). As approaches to databased value creation are still nascent or under development, studies reflecting the diversity of data-driven value creation strategies in organizational settings are scarce (Baecker *et al*., 2025). There remains a gap in understanding the business capabilities necessary to create value from data (Bisswang *et al*., 2025).

Furthermore, there is a scarcity of studies synthesizing knowledge on the topic. To the best of our knowledge, the most recent bibliometric study focused on this topic and context is by Ardito, Scuotto, Del Giudice, and Petruzzelli (2019). Other recent bibliometric analyses address D&A in specific areas - such as human resources (Fauzi, Kamaruzzaman, & Rahman, 2022), fintechs (Botoc, Khaled, Milos, & Bilti, 2023), and performance measurement (Sardi, Sorano, Cantino, & Garengo, 2023) - but do not offer a holistic view. Since 2019, research has evolved significantly, and the lack of an uptodate mapping hinders understanding of the existing literature and the identification of research gaps. Organizing the scientific body of knowledge on the topic is essential for advancing the field (Paré, Trudel, Jaana, & Kitsiou, 2015).

In light of these theoretical gaps, the research question is: What is the state of knowledge on D&A in the research field of business strategy and information systems management? Accordingly, the objective of this study is to "map the state of knowledge on D&A in the research field of business strategy and information systems management."

Bibliometrics was adopted to examine and understand the body of knowledge on D&A. Bibliometric analysis has been increasingly used in information systems research (Abedin, Jafarzadeh, & Olszak, 2021) to assess quality, impact, and influence of authors, journals, and institutions in a specific research area, such as BDA (Aboelmaged & Mouakket, 2020; Ardito *et al*., 2019) and AI (Bawack, Wamba, Carillo, & Akter, 2022).

The findings of this study provide an overview of the body of knowledge on D&A in the field of business strategy and information systems management. In summary, the theoretical contributions are: (i) understanding the state of knowledge; (ii) mapping scientific production; (iii) organizing and discussing visual maps that identify four co-citation clusters indicating the

most important and influential publications, as well as five clusters in the keyword cooccurrence analysis indicating predominant themes; and (iv) proposing a research agenda to guide future inquiry. These findings can generate insights for researchers to explore theoretical gaps and for managers (e.g., CIOs, CDOs, or CAOs) to gain a holistic understanding of D&A in organizational environments.

This study is structured as follows: first, the method, design, and procedures of the bibliometric study are detailed. Next, the results of the analyses are discussed. Finally, the contributions and limitations of this study are described.

2 Method

A systematic literature review is a strategy adopted in numerous studies on D&A in the fields of business strategy and information systems management (for example: Abraham, Schneider, & vom Brocke, 2019; Alhassan, Sammon, & Daly, 2018; Albqowr, Alsharairi, & Alsoussi, 2022; Ardito *et al*., 2019; Brous, Janssen, & Vilminko-Heikkinen, 2016; Fiorini *et al.*, 2018; Günther *et al.*, 2017; Mikalef, Pappas, Krogstie, & Giannakos., 2018; Rialti, Marzi, Ciappei, & Busso, 2019; Surbakti, Wang, Indulska, & Sadiq, 2020; Walter *et al.*, 2021; Bawack *et al*., 2022; Reddy *et al*., 2022; Javed & Akhlaq, 2024). However, researchers may employ different qualitative and quantitative literature review approaches to understand and organize prior findings. In this work, we adopted a quantitative approach by employing bibliometric analysis.

Overall, the planning and execution of analyses follow the guidelines for conducting a Systematic Literature Review (SLR) presented by Webster and Watson (2002), Okoli and Schabram (2010), Paré *et al*. (2015), and Aria and Cuccurullo (2017). The study was conducted according to the stages, phases, and procedures indicated in **Table 1.**

Table 1. **Study plan.**

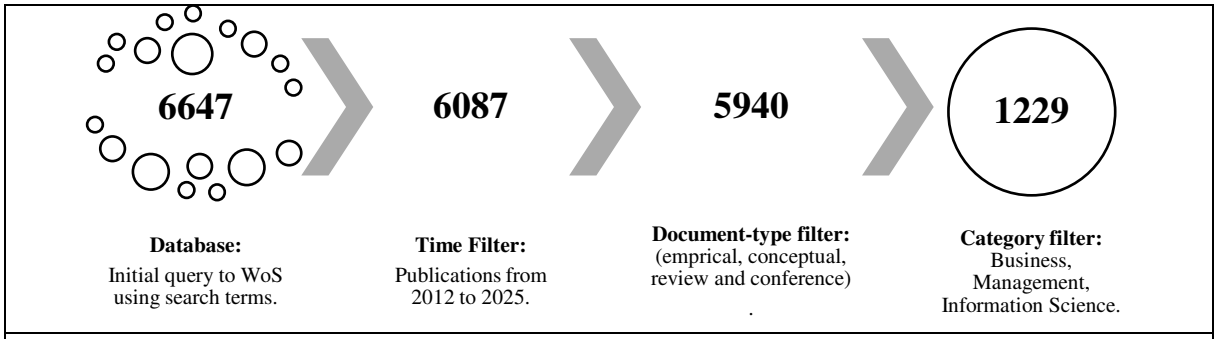
Stage| Phase	Procedure
1. Identification of the research problem	- Mapping of the debate agenda on the topic. - Identification of gaps, research question, and review objective.
2. Protocol development	- Planning of search procedures and source selection.
3. Literature collection	- Execution of the source-selection protocol.
4. Descriptive analysis of the literature	- Bibliometric analysis of scientific production. - Thematic mapping.
5. Thematic analysis of the literature	- Interpretation and discussion of the bibliometric study. - Synthesis of the research agenda.

First, bibliometric analysis was undertaken, as it has the potential to introduce a systematic, transparent, and reproducible review process based on the statistical measurement of science, scientists, or scientific activity (Aria & Cuccurullo, 2017). No matter how comprehensive a literature review aiming to build a reference framework for any research field may be, it can still be subject to author bias; therefore, the methodological strategy of employing bibliometric analysis serves precisely to mitigate limitations and simplify the overall visualization of the current state of knowledge on the topic (Nayak, Bhattacharyya, & Krishnamoorthy, 2022).

The data sample for this bibliometric study was obtained by querying the main Web of Science (WoS) databases for publications from 2012 to 2025. WoS was chosen due to its relevance for retrieving bibliographic sources of scientific publications, as noted by other systematic literature reviews and bibliometric studies in the field of data analytics and information systems (Ardito *et al*., 2019; Bawack *et al*., 2022; Günther *et al*., 2017; Liu, Yin, Liu, & Dunford, 2015; Rialti *et al*., 2019; Walter *et al*., 2021). The choice of WoS over other databases (such as Google Scholar or Scopus) is justified by its provision of higherquality bibliometric information, owing to its lower rate of duplicate records and greater coverage of high impact journals (Aria, Misuraca, & Spano, 2020; Bawack *et al*., 2022).

The initial search term was based on the keywords defined in the protocol according to the target concepts identified. The search string was used to query the topic, title, keywords, and abstracts of all documents in the WoS collection. The initial query performed on the WoS platform yielded 6,642 documents. Only scientific documents published from 2012 onward (the publication year of the seminal article by Chen, Chiang, and Storey, "Business intelligence and analytics: from big data to big impact" in MIS Quarterly — which spurred organizational implications research) were considered, reducing the set to 6,082 documents.

Figure 1 presents the search and sample selection protocol.



Search terms adopted (*string*): ((“data strategy” OR “analytical strategy”) OR (“data governance” OR “analytics governance” OR “big data governance”) OR (“data-driven culture” OR “analytical culture”) OR ((“data analytics capabil*” OR “data analytical capabil*” OR “big data analytics capabil*” OR “business analytics capabil*”)) OR ((“organizational agility” OR “agility”) AND (“data analytic*” OR “big data” OR “business analytics”)) OR ((“corporate performance management” OR “business performance management”) AND (“data analytic*” OR “big data” OR “business analytics”)) OR (“Competitive advantage” AND (“data analytic*” OR “big data” OR “business analytics”)).

Language: english, portuguese and spanish.

Figure 1. Sample selection process and protocol.

Additional criteria were applied. We sought documents (empirical, conceptual, or review articles) published in recognized journals or conferences with open access to their full content. Book chapters, editorials, letters, news items, and all non–peerreviewed publications were excluded to ensure an examination of high quality research (Bawack *et al*., 2022; Liu *et al*., 2015). After this filter, 5,935 documents remained. We then excluded those outside the organizational context - based on the categories Business, Management, and Information Science - such as works focused on computer science, medical and health sciences; social sciences; engineering; and technical applications of BD, analytics, machine learning, or AI. This refinement yielded a final sample of 1,229 documents in English, Portuguese, or Spanish.

With this sample in hand, we conducted the quantitative (bibliometric) analysis of the literature, following the approach of Ardito *et al*. (2019). In this quantitative stage, we did not restrict the journal list by impact factor cutoffs or publication period, given the recent emergence of the topic.

3 Analysis and Discussion of Results

Bibliometric analysis is the application of quantitative tools (general descriptive statistics, such as identifying leading authors, journal publications, etc.) to the study of scientific communications (Liu *et al*., 2015), which helps analyze large volumes of data and gain an understanding of the field of study (Abedin *et al*., 2021). This bibliometric study began with a descriptive analysis and a broad mapping of the scientific output in the research domain. Next, a thematic analysis was conducted by mapping the most frequent keywords. Finally, we analyzed the most developed and relevant themes in the field in order to cross-reference these

results and generate inferences and insights for the development of the research agenda. Throughout this study, we discussed how these findings delineate the state of knowledge on the topic, indicating opportunities for future research.

3.1 Scientific Production

In the literature, there is no consensus on which indicator can fully represent the bibliometric outcomes of a document set. Researchers assess results differently according to their interpretation. While some may emphasize the number of publications as a measure of productivity, others may regard the number of citations as a measure of impact (Abedin *et al.*, 2021; Beydoun, Abedin, Merigó, & Vera, 2019). This article focuses on the number of publications and citations, citations per article, and the h-index.

Based on the overall information from the 1,229 retrieved documents, the corpus is composed primarily of articles (86.76%), with smaller shares of proceeding papers (8.41%) and review articles (6.69%). **Figure 2** depicts the research areas with more than ten publications.

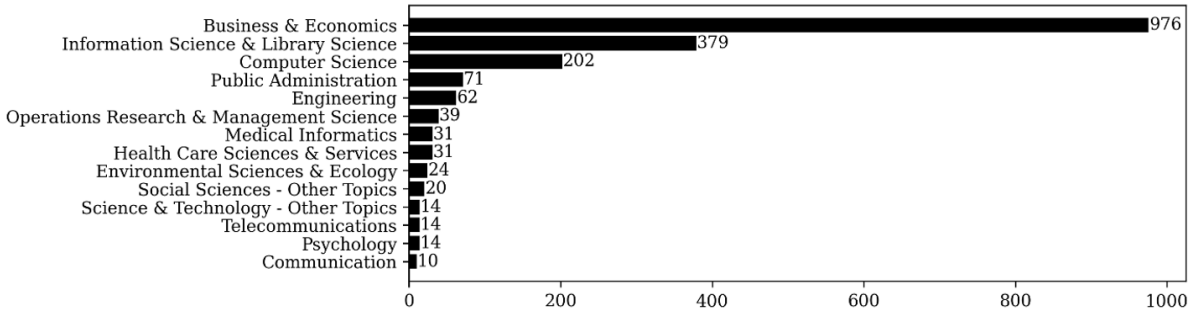


Figure 2. Number of articles by category (Source: WoS, 2025).
Note. Only categories with more than ten published articles are shown.

It is noteworthy that the topic exhibits an interdisciplinary character, as many works appear in more than one category. Business & Economics, Information Science & Library Science, and Computer Science predominate, which is to be expected given the centrality of these fields to discussions of D&A. There is also a significant presence of areas such as Public Management, Engineering, and Operational Research & Management Science, reflecting growing interest in data-driven management.

On the other hand, the substantial participation of fields such as Medical Informatics, Health Sciences, and Environmental Sciences indicates that research needs extend beyond the corporate context and into sectors essential to society. This trend can be attributed to recent advances in AI and BDA technologies, with potential applications in smart health and smart cities. In both cases, data interoperability and governance become central challenges, requiring new analytical approaches and organizational strategies.

3.1.1 Evolution of Scientific Production

Regarding temporal evolution, there has been a consistent increase in the number of publications since 2012, culminating in a peak of 219 publications in 2024. This growth reflects the innovative nature and rising importance of the topic, especially following the COVID19 pandemic, which accelerated digital transformation and solidified D&A as a priority in organizations. The expectation is that scientific output on this topic will continue to expand in the coming years, keeping pace with the demands of an increasingly data-driven environment.

The number of publications and citations is shown in **Figure 3.**

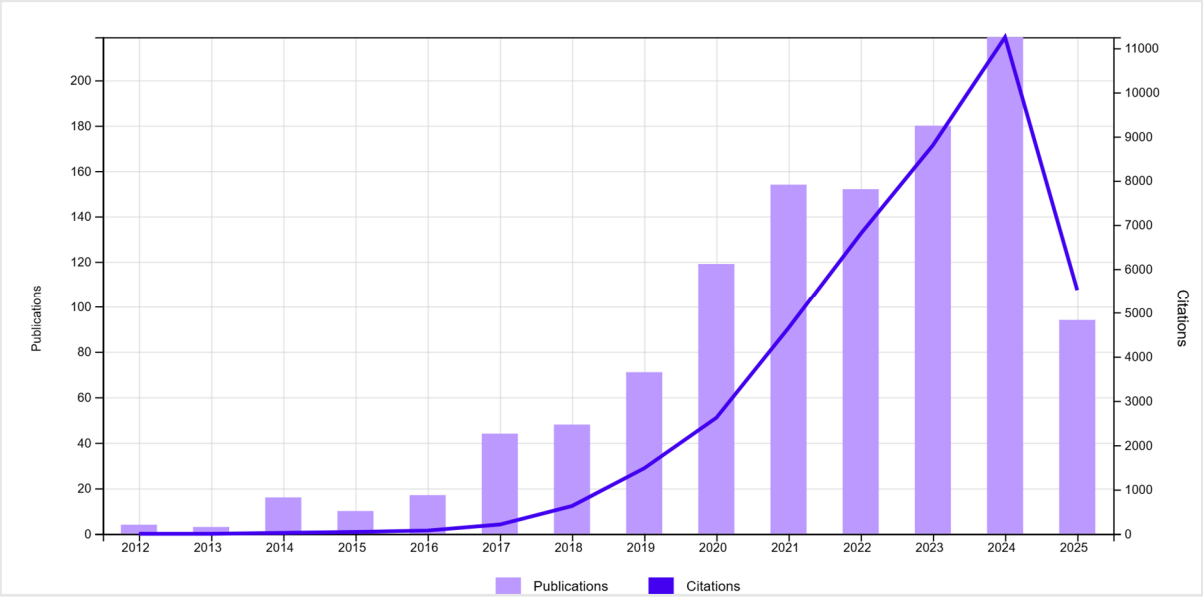


Figure 3. Evolution of publication and citation counts (Source: WoS, 2025).

A total of 42,085 citations were observed (37,085 excluding self citations), with an average of 35.61 citations per article and an hindex of 98, indicating that research on this topic has achieved high relevance.

Interest in this theme first emerged in 2012, when Harvard Business Review published three influential articles in the professional domain: "Big Data: The Management Revolution" (McAfee & Brynjolfsson, 2012), "Data Scientist: The Sexiest Job of the 21st Century" (Davenport & Patil, 2012), and "Making Advanced Analytics Work for You" (Barton & Court, 2012). In the scientific realm, MIS Quarterly released a special issue on business intelligence, led by the article "Business Intelligence and Analytics: From Big Data to Big Impact" (Chen, Chiang, & Storey, 2012). The following year, in 2013, the Journal of Business Logistics published the editorial "Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management" (Waller & Fawcett, 2013).

From 2017 onward, there was a substantial jump in scientific production on the topic. This surge may have been driven by several special issues, such as: "Special Issue: Big Data Analytics and Business Process Innovation" (Wamba, 2017) in Business Process Management Journal; "Special Issue: Big Data and Performance" (Sena, Demirbag, Bhaumik, & Sengupta, 2017) in British Journal of Management; "Special Issue: Strategic Value of Big Data and Business Analytics" (Chiang, Grover, Liang, & Zhang, 2018) in Journal of Management Information Systems; and "Special Issue: In (Big) Data We Trust: Value Creation in Knowledge Organizations - Introduction to the Special Issue" (De Mauro, Greco, Grimaldi, & Ritala, 2018) in Information Processing & Management.

During the pandemic, key special issues included: "Special Issue: Big Data Analytics and Artificial Intelligence to Combat a Pandemic" (Gupta *et al.*, 2020) in Journal of Data, Information and Management; "Special Issue: Cognitive Big Data Analytics for Intelligent Information Systems" (Elhoseny, Hassan, & PejicBach, 2020) in Information Systems and eBusiness Management and Technological Forecasting & Social Change. More recently, notable issues and articles are: "Towards Designing Valuable and Explainable Data-Driven Systems" (Bellatreche, Cerquitelli, Chiusano, & Wrembel, 2022) in Information Systems Frontiers; "Health Analytics and Theorizing" (Baird, Xia, & Kohli, 2023) in Journal of the Association for Information Systems (JAIS); "Information Systems and Data Work in Healthcare" (Bertelsen, Bossen, Pine, & Chen, 2024) in Scandinavian Journal of Information

Systems; and "Generative AI, Foundation Models, and Deep Learning with Applications to Business Analytics" (Abbasi, Chen, Li, & Liu, 2025) in INFORMS Journal on Data Science.

3.1.2 Key Journals and Publications

It is worth noting that a variety of journals contributed to the publication of the 1,229 documents, demonstrating how widely the topic is disseminated in the existing literature. The top seven journals leading publications on this subject are prestigious outlets in the information systems field, with high impact metrics (h-index), and have actively fostered the scientific communication of work on this topic. Several have also spearheaded special issues, as noted above. This list serves as a potential indicator of key sources and of promising venues for future research publication and dissemination.

Table 2 lists journals with more than fifteen publications during the period.

Table 2. **Journals with the highest number of publications** (N = 1,229 documents).

Publication Titles	H-index	N	% do corpus
Technological Forecasting and Social Change	209	50	4.42
Journal of Business Research	292	47	4.16
Journal of Enterprise Information Management	89	29	2.56
Business Process Management Journal	102	28	2.48
International Journal of Information Management	196	28	2.48
Information Management	204	25	2.21
IEEE Transactions on Engineering Management	117	24	2.12
Journal of the American Medical Informatics Association	184	24	2.12
Management Decision	138	22	1.95
Business Strategy and the Environment	173	17	1.50
Industrial Marketing Management	187	17	1.50
Benchmarking an International Journal	89	16	1.42
European Journal of Innovation Management	88	16	1.42

Note. Only journals with more than 15 publications are included.

In **Table 3**, the articles with the highest citation counts are presented. This set of 15 articles accounts for approximately 25% of the total citations in the sample. Most of these articles treat BD or business analytics as a resource or dynamic capability, examining its components and its effects on performance, innovation, and value creation.

The most cited work in the sample, by Verhoef *et al.* (2021), is titled "Digital transformation: A multidisciplinary reflection and research agenda," with 1,951 citations. This study identifies three stages of digital transformation - digitization, advanced digitization, and full digital transformation - and outlines strategies for successful digital transformation. It discusses how digital transformation requires specific organizational structures and proposes a research agenda.

The second most cited article, by Wamba *et al.* (2017), "Big data analytics and firm performance: Effects of dynamic capabilities," has 1,218 citations. It proposes a BDA capability model grounded in the resource-based view, investigating both the direct effects on firm performance and the mediating role of process oriented dynamic capabilities.

The third most cited article, by Gupta and George (2016), "Toward the development of a big data analytics capability," with 813 citations, explores the development of analytic capabilities in BD and their strategic role for organizational competitiveness. The paper presents a robust conceptual model, supported by empirical research, detailing the essential elements for building an effective BDA capability and emphasizing its importance for competitive advantage.

Table 3. **Articles with more than 350 citations on the topic** (N = 15 of 1,229 documents).

Article Title	N
1. Digital transformation: A multidisciplinary reflection and research agenda (Verhoef *et al*., 2021).	1951
2. Big data analytics and firm performance: Effects of dynamic capabilities (Wamba *et al*., 2017).	1218
3. Toward the development of a big data analytics capability (Gupta e George, 2016).	813
4. Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices (El-Kassar e Singh, 2019).	752
5. Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations (Wang, Kung, & Byrd, 2018).	745
6. Big data and predictive analytics for supply chain and organizational performance (Gunasekaran *et al*., 2017).	689
7. Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities (Mikalef *et al*., 2020).	579
8. How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management (Chen *et al*., 2015).	534
9. Creating Strategic Business value from big data analytics: A Research Framework (Grover *et al*., 2018).	522
10. Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance (Mikalef e Gupta, 2021).	520
11. Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture (Dubey *et al*., 2019b).	498
12. Big data analytics capabilities and innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment (Mikalef *et al*., 2019b).	464
13. Can big data and predictive analytics improve social and environmental sustainability? (Dubey *et al*., 2019c)	444
14. Big data analytics capabilities: a systematic literature review and research agenda (Mikalef *et al*., 2018)	443
15. Big data analytics capabilities and knowledge management: impact on firm performance (Ferraris *et al*., 2019)	394

Note: Only articles with more than 350 citations were considered.

3.1.3 Diffusion and Research Centers

Table 4 presents the analysis of countries with more than ten publications. Although the research is geographically widespread, it is noticeable that the greatest contribution comes from traditional European research centers. Interestingly, Asian scientific output exceeds that of North America. Additionally, Australian and Brazilian scientific production is also significant.

Table 4. **Number of publications by country.**

Continent (N)	Country (N)
Europa (389)	England (174); Italy (81); France (80); Germany (54)
Asia (309)	China (199); India (110)
North America (239)	USA (195); Canada (44)
Oceania (76)	Australia (76)
South America (55)	Brazil (55).

Figure 4 depicts the select group of 32 authors who contributed most to the topic, considering those with at least five publications. Leaders such as Akter, Mikalef, Wamba, Maçada, and Chatterjee each contributed more than ten publications.

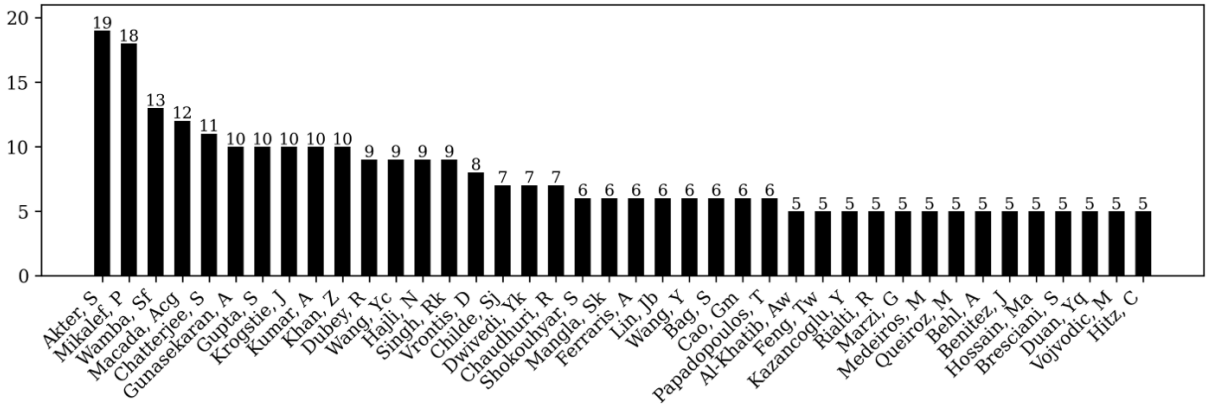


Figure 4. Number of publications per author.
Note. Only authors with five or more publications are shown.

Since this study was conducted in Brazil, it is noteworthy that three Brazilian researchers (Maçada, A. C. G.; Medeiros, M. M.; and Queiroz, M. M.) appear among these international leaders, contributing to the national research advancement. Moreover, the Federal University of Rio Grande do Sul (UFRGS) ranks among the top 20 institutions in publication output, alongside other globally prominent universities. However, there is a long tail of authors - 3,059 in total - who contributed only a single article, indicating that few scholars have specialized in this topic; thus, the scientific leadership in D&A within business strategy and information systems can be recognized.

Figure 5 shows the affiliations with the highest publication counts, considering only institutions with more than ten publications.

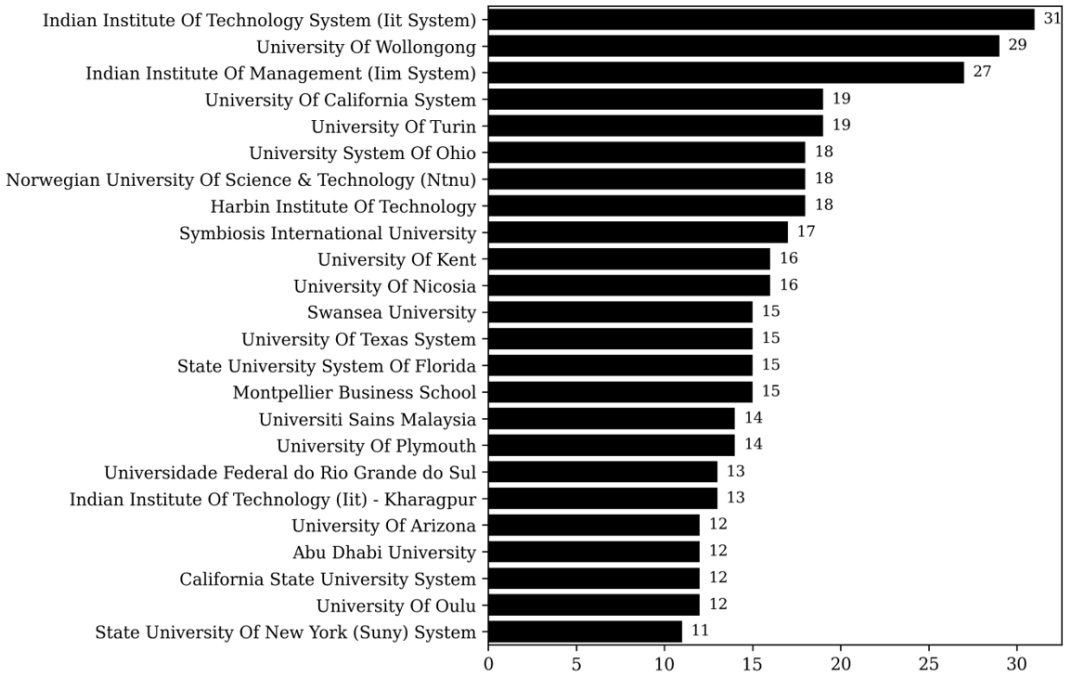


Figure 5. Number of publications by institutional affiliation.
Note. Only institutions with more than ten publications are included.

These descriptive analyses reveal the body of scientific knowledge: production and impact demonstrate growing interest in the topic, predominantly within the management discipline. This growth is fueled by special issues - particularly in Technological Forecasting and Social Change, which leads in volume and includes the highly cited works of Wang *et al.* (2018) and

Dubey *et al*. (2019c). A potential research nucleus is evident in Europe, China, and the United States, where publication counts are highest, and the leading authors and institutions are identified. Below is the mapping of co-cited references.

3.2 Co-Citation Cluster Analysis

Cocitation analysis reveals groups of documents that represent different streams within the research domain. Collectively cited documents form the intellectual base of a knowledge domain. Following Ardito *et al*. (2019), we conducted document co-citation analysis on the sample's reference lists to identify major clusters representing the state of D&A research. We used VOSviewer 1.6.20, which generates maps via clustering techniques (Van Eck, Waltman, Dekker, & Van Den Berg, 2010). To normalize cooccurrence frequencies, we used the "association strength," defined as the ratio of the observed cooccurrences of items A and B to the expected cooccurrences under statistical independence (Van Eck & Waltman, 2010). VOSviewer positions items on the map by minimizing the weighted sum of squared distances between all item pairs.

Figure 6. Map of co-citation clusters in the sample.

To construct **Figure 6**, we used the references from the sample corpus. In total, 60,830 references were recorded. Of these, we analyzed only those with a frequency of 20 or more occurrences. Larger nodes indicate documents receiving more citations; thicker links show stronger co-citation between connected nodes. Thus, the map comprises 316 reference nodes, 38,410 links, and four-color coded clusters (blue, yellow, red, and green). Due to the size of each cluster, only the main aspects are discussed:

(i) **Yellow cluster:** Represents foundational articles on the organizational theories most frequently used to explain the phenomena in our sample - namely, the resource-based view (RBV) (Barney, 1991; Grant, 1991) and dynamic capabilities view (DCV) (Eisenhardt & Martin, 2000; Teece, 2007) - as well as other contextual works from professional literature sources that spurred the theme's early diffusion (e.g., Harvard

Business Review, MIT Sloan). RBV appears in 282 documents and DCV in 279, together covering 46% of the sample.

(ii) **Red cluster:** Gathers the articles that have served as the predominant methodological foundation for others, such as Fornell and Larcker (1981) and Podsakoff, MacKenzie, Lee, & Podsakoff (2003). Notably, Partial Least Squares Structural Equation Modeling (PLS-SEM) is the dominant method, used in 245 publications (20% of the sample).

(iii) **Green cluster:** Consolidates the most cited articles on the topic, appearing in leading outlets of the field (e.g., Braganza *et al.*, 2017; CôrteReal *et al.*, 2017; Dubey, Gunasekaran, & Childe, 2019a; Gupta & George, 2016; Mazzei & Noble, 2017; Suoniemi *et al.*, 2020; Wamba *et al.*, 2017; Shamim, Zeng, Shariq, & Khan, 2018).

(iv) **Blue cluster:** Groups works that likely served as references for studies analyzing the topic from the perspective of organizational agility (e.g., Lu & Ramamurthy, 2011; Overby, Bharadwaj, & Sambamurthy, 2006; Sambamurthy, Bharadwaj, & Grover, 2003). The primary source here is MIS Quarterly.

Co-citation analysis thus identifies clusters of articles frequently cited together, indicating thematically or methodologically linked groups - i.e., the most important and influential works on the topic.

3.3 Keyword Frequency Analysis

Because keywords convey central content information, a keyword frequency analysis can track research topics and the evolving frontiers of a knowledge domain (Liu *et al.*, 2015). For this analysis, we used the author provided keywords, without translation. The total keyword corpus includes 6,750 terms. **Figure 7** show word cloud of the 100 most frequent author keywords.

Figure 7. Word cloud of the 100 most frequent keyword terms**.**
Note: The font size in the word cloud is associated with the frequency of a given term in the sample.

Figure 8 highlights the 10 most frequent words (754 terms, 12% of the corpus).

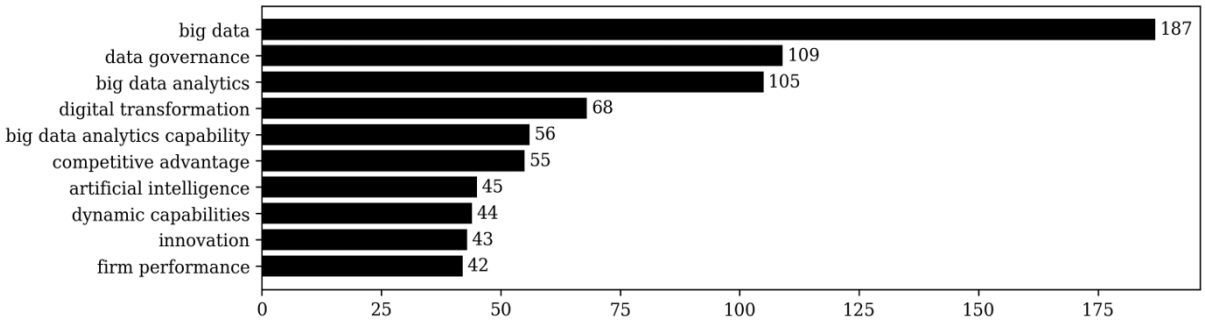


Figure 8. Top 10 most frequent words in keyword terms.

The objective of this analysis was to identify the trend of keywords with the greatest prevalence in D&A research. The terms “big data”, “data governance”, “big data analytics”, “digital transformation”, “big data analytics capability”, “competitive advantage”, “artificial intelligence”, “dynamic capabilities”, “innovation”, and “firm performance” adequately represent the target context of this study. Both in terms of context and theoretical concepts, they largely represent the object of analysis.

Next, the co-occurrence of keywords is analyzed to identify clusters.

3.4 Keyword Cluster Mapping

Using the bibliometric mapping program (VOSviewer), the data obtained were represented graphically. The co-occurrence map facilitates the identification and processing of observed terms, allowing for further identification of potential thematic areas and the investigation of specific terms. **Figure 9** shows the map of the most frequent keyword clusters. The larger the node, the more co-occurrences are counted in the sample; the thicker the link, the more co-occurring nodes were connected.

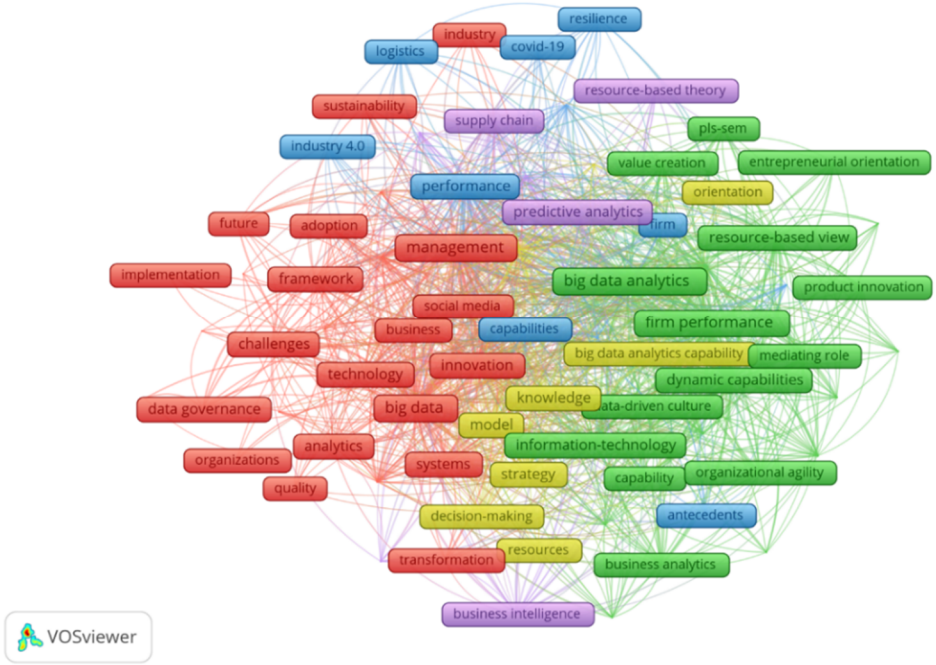


Figure 9. Cluster Map of Author-Keyword Terms

For the network construction, we included only those terms with a frequency of 25 occurrences or more - well above the recommended minimum of five occurrences (Appio, Cesaroni, & Di Minin, 2014). After standardization (e.g., merging "dynamic capability" and "dynamic capabilities") and excluding methodological labels (e.g., "literature review," "case study," "structural equation modeling"), 78 keywords remained. VOSviewer then generated five clusters, with 2,542 inter-term links and a total link strength of 18,370. The most frequent term was "big data" (402 occurrences), followed by "firm performance" (295), "management" (291), "BDA" (284), and "dynamic capabilities" (234) - each also ranking highest in link strength (1,908; 1,989; 1,732; 1,778; and 1,566, respectively).

Below, **Table 5** details the five clusters, listing their associated keywords and illustrative reference examples. Due to the large number of articles in each cluster, only a few are highlighted for illustration.

Table 5. **Keyword-term cluster analysis** (N = 78 terms).

Cluster Summary	N	Author-Keywords	Illustrative References
#1: Governance and management of data, analytics, information, and AI for innovation and digital transformation.	27	Adoption; Analytics; Artificial Intelligence; Artificial-Intelligence; Big Data; Business; Challenges; Data Governance; Design; Digital Transformation; Framework; Future; Governance; Implementation; Industry; Information; Innovation; Management; Opportunities; Organizations; Privacy; Quality; Social Media; Sustainability; Systems; Technology; Transformation.	Janssen *et al*., 2020; Verhoef *et al*., 2021; Mikalef e Gupta, 2021.
#2: Big data analytics for performance, organizational agility, competitiveness, and value creation.	23	Absorptive-Capacity; Big Data Analytics; Business Analytics; Business Value; Capability; Competitive Advantage; Data-Driven Culture; Dynamic Capabilities; Entrepreneurial Orientation; Firm Performance; Information-Technology; Information-Technology Capability; Intelligence; Knowledge Management; Market Orientation; Mediating Role; Organizational Agility; Organizational Performance; PLS-SEM; Product Innovation; Resource-Based View; Value Creation.	Ahmad & Akbar, 2021; Gupta e George, 2016; Mikalef *et al*., 2020; Wamba *et al*., 2017; Suoniemi *et al*., 2020.
#3: Data analytics for data integration, agility, resilience, and performance.	12	Agility; Antecedents; Capabilities; Covid-19; Firm; Industry 4.0; Integration; Logistics; Performance; Perspective; Resilience; Supply Chain Agility	Chen *et al*., 2015; Dubey *et al*., 2019a; Gunasekaran *et al*., 2017.
#4: Strategy, data-analytics capability, and decision-making.	9	Big Data Analytics Capabilities; Big Data Analytics Capability; Decision-Making; Impact; Knowledge; Model; Orientation; Resources; Strategy.	Ferraris *et al*., 2019; Medeiros *et al*., 2020; Mikalef *et al*., 2019a; Reddy *et al*., 2022.
#5 Business analytics intelligence, data science, and predictive analytics.	7	Business Intelligence; Data Analytics; Data Science; Predictive Analytics; Resource-Based Theory; Supply Chain; Supply Chain Management.	Dubey *et al*., 2019c; Chen *et al*., 2016; Wamba, Gunasekaran, Dubey, & Ngai, 2018.

The next section presents the thematic mapping of knowledge on the topic.

3.6 Thematic Mapping

Following the identification of the five clusters based on the keyword link strength analysis, we proceeded to map the most frequently addressed themes in the publications. For this purpose, we used the *Bibliometrix* package in *R Studio*. According to LópezRobles, OtegiOlaso, Porto Gómez, and Cobo (2019), this tool enables the identification of themes and subdomains through clustering.

In **Figure 10**, four research themes are presented, separated into quadrants: **Motor Themes**, **Basic Themes**, **Emerging or Declining Themes**, and **Niche Themes**.

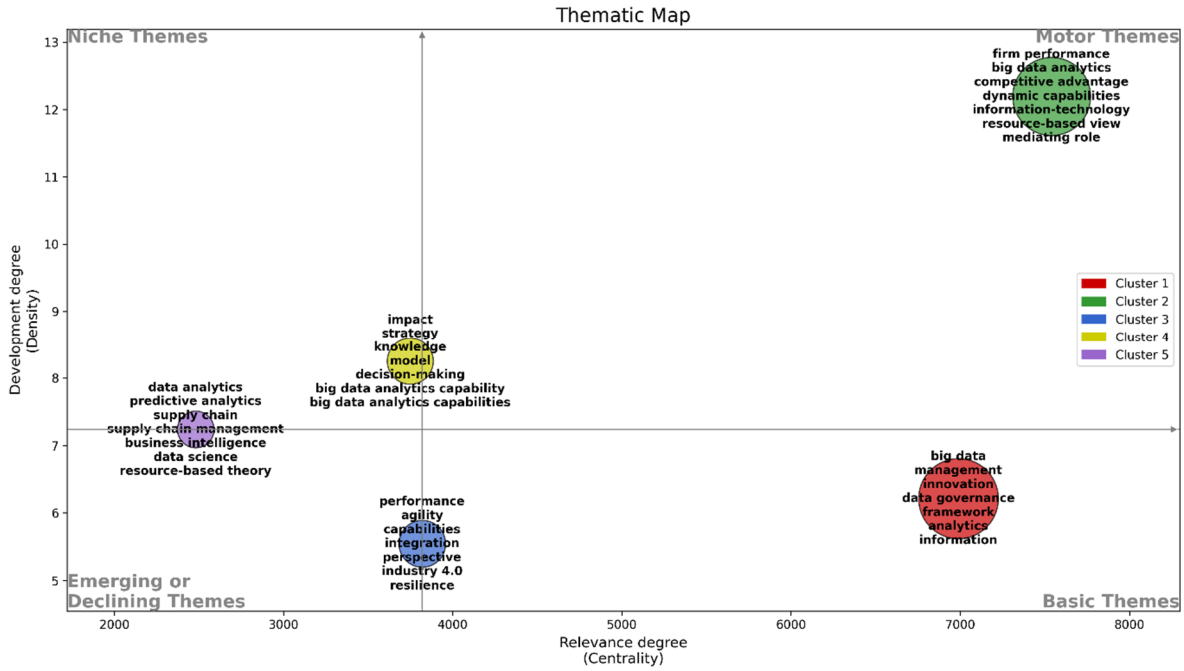


Figure 10. Cluster map of author-keyword terms.

This centrality-and-density thematic analysis yields several important findings and insights, discussed in detail below.

3.6.1 *Motor Themes:* key concepts due to strong centrality and high density

The first quadrant highlights ***cluster* #2 (green)** which addresses the relationship among "big data analytics", "information technology", "firm performance", and "competitive advantage", forming the most consolidated and mature core of the field. The presence of terms such as "dynamic capabilities", "resource-based view", and "mediating role" underscores the predominant theoretical anchoring, indicating a robust and well-structured body of knowledge. The interconnection of these concepts suggests that current research focuses on demonstrating how leveraging resources and dynamic capabilities in BDA can generate superior performance and competitive advantage for organizations. The concentration of organizational resource and dynamic capability theories and the use of partial least squares structural equation modeling indicate opportunities to investigate these concepts through new theoretical lenses and methodological approaches.

3.6.2 *Basic Themes*: relevant concepts for the field

In the second quadrant lies ***cluster* #1 (red)** covering BD and AI and including terms such as "big data", "management", "innovation", "data governance", "framework", "analytics", and

"information". Although considered central to the field, these topics still lack depth. They are broad, foundational themes that structure the debate but exhibit conceptual and empirical gaps. This finding represents an important opportunity for theoretical and empirical advancement, especially in research exploring the antecedents, mechanisms, and outcomes of governance and management (of data, analytics, and information) in the context of BD and AI for datadriven innovation.

3.6.3 *Emerging or Declining Themes*: themes with low density and centrality

The third quadrant gathers two clusters. **Cluster #3 (blue)** with terms such as "capabilities", "performance", "agility", "integration", "resilience", "Industry 4.0" — may indicate that, although relevant, this cluster is still in early development stages and requires greater integration with the field's core debates.

And **cluster #5 (purple)** covering "data analytics", "predictive analytics", "supply chain management", as well as "business intelligence", "data science", and "resource-based theory", may represent emerging niches needing stronger theoretical and empirical articulation, or topics that were once ascendant but have since lost prominence.

3.6.4 *Niche Themes*: strongly related but peripheral topics

In the fourth quadrant is **cluster #4 (yellow)**, which highlights themes such as "impact", "strategy", "knowledge", "model", "decision-making", and "big data analytics capabilities". These topics have a consistent internal conceptual articulation but remain peripheral to the major debates in the area. This suggests they may represent specialized subfields or conceptual approaches not yet widely integrated into the mainstream. However, their density indicates potential for greater relevance, especially if connected to more central themes data governance and analytics, innovation, organizational performance, and competitive advantage. Notably, this cluster sits on the boundary between the niche themes and motor themes quadrants. This is an important discovery, as it directly aligns with this study's rationale and objective: exploring the knowledge frontier of D&A in business strategy and information systems.

In the next section, we present the **research agenda**, consolidating the main challenges for advancing knowledge on the topic.

3.7 Research Agenda

The integrative analysis of the results revealed theoretical gaps and research opportunities in D&A and its emerging intersections with AI. To advance the fields of business strategy and information systems management, this agenda proposes a set of research opportunities structured around the five thematic clusters identified. **Table 6** outlines twenty (20) research questions for the agenda.

The **first cluster** addresses the inherent complexity of governance and management in the context of D&A and AI. Despite its centrality, significant conceptual and empirical gaps remain in understanding its antecedents, mechanisms, and outcomes, as highlighted by Abraham *et al.* (2019), Alhassan *et al.* (2018), Brous *et al.* (2016), Fattah (2024), Janssen *et al.* (2020), Medeiros *et al.* (2020), and Salerno & Maçada (2025b). The proposed questions investigate the impact of data quality on D&A and AI adoption, risk mitigation through governance in big-data and AI environments, governance of generative and agentic AI in business, the effect of data, analytics, and AI governance on innovation, and the influence of data debt on organizational risk.

The **second cluster** explores the use of D&A for organizational performance, agility, competitiveness, and value creation, with exemplars in Al-Omoush (2024), Medeiros & Maçada (2022), and Zhang *et al*. (2025). Although this represents a well-established research core - strongly grounded in dynamic capabilities and the resource-based- view - a predominance of specific theoretical and methodological approaches limits broader understanding. We suggest triangulation with alternative organizational theories and the adoption of mixed methods- research.

Table 6. **Research agenda.**

Cluster	**Research Opportunities**
#1. Governance and management of data, *analytics*, information, and AI for innovation and digital transformation.	(1) What is the impact of data quality on the use of data analytics and AI? (2) How can governance and management mechanisms mitigate risks to information security and personal data privacy in organizational environments involving BDA and AI? (3) What is the relationship between data governance and management and the adoption and governance of generative and agentic AI in different types of businesses? (4) What is the effect of data governance, analytics, and AI on innovation? (5) How can data debt (low-quality data, data silos, lack of governance, legacy systems, and low-quality analytical modeling) increase risk and reduce organizational agility?
#2. *Big data analytics* for organizational performance and agility, competitiveness and value creation.	(6) In addition to organizational theories based on resources, knowledge, and capabilities, explaining the adoption and management of Data Analytics and AI in light of other organizational theories can generate original contributions. For example, triangulating these with informational, cognitive, and behavioral theories. (7) In addition to structural equation modeling, using other methods to analyze the adoption and management of Data Analytics and AI can generate original contributions. For example, triangulating mixed methods with qualitative approaches, or other quantitative approaches such as experimental methods.
#3. *Data analytics* for data integration, agility, resilience, and performance.	(8) How does the use of data analytics and AI optimize data integration, agility, and resilience in organizational environments and business ecosystems? (9) What role does transactional data quality play in the effectiveness of data analytics and AI in predicting and mitigating operational risks in the supply chain, and how does this translate into cost reduction, sustainability, and value? (10) How can a data-driven culture foster data orchestration and sharing, as well as the implementation of analytics and AI capabilities in organizational environments and business ecosystems?
#4. Strategy, data analytics and decision-making.	(11) What are the relationships, similarities, and differences, between data strategy, analytics strategy, and AI strategy in organizations? And how can different types of strategies generate organizational and competitive value? (12) What organizational factors can hinder or facilitate the alignment between business, digital, data, and AI strategies? (13) How can strategies for sharing, protecting, and monetizing data assets generate organizational and competitive value? (14) How do data-driven leadership and mindsets affect data-driven decision-making for formulating and executing business strategy? (15) To what extent can data literacy drive the adoption and use of AI tools in organizations? (16) How can individual strategic competencies in data and AI (such as data literacy, prompt engineering, and agentic AI engineering) favor the execution of business strategy?
#5. Business analytics, data science, and predictive analytics.	(17) How can the use of AI tools benefit the use of descriptive analytics and data visualization techniques in organizations? (18) How can the use of AI benefit the use of predictive analytics techniques to anticipate risks and opportunities in business operations? (19) What is the impact of the use of AI tools on the automation of prescriptive analytics techniques for optimization and innovation in business processes? (20) How can the dark side of data science and AI (algorithmic bias, personal data privacy issues, misinformation, overreliance on data and AI) pose risks to organizational and competitive value creation?

The **third cluster** investigates the role of D&A in data integration, agility, resilience, and performance. Despite its strategic relevance, this cluster remains in early development stages, with limited connection to core business strategy debates. Studies by Albqowr *et al*. (2022), Bhargava *et al*. (2020), Dubey *et al*. (2019a), and Salerno & Maçada (2025a) contribute to understanding the challenges in this area. The research questions aim to understand how D&A and AI optimize data integration, agility, and resilience within ecosystems. They propose investigating the role of transactional data quality in the effectiveness of D&A and AI for risk prediction and mitigation, and the impact of a data-driven culture on data orchestration and sharing in bigdata and AI environments.

The **fourth cluster** highlights the intrinsic relationship among strategy, data analytics capability, and decision-making. However, despite its internally consistent conceptual framing, the themes in this cluster remain somewhat peripheral to the major strategic debates, requiring greater visibility and integration. Emerging studies on data strategy by Baecker *et al*. (2025), Bhisikar (2024), Bisswang *et al*. (2025), Medeiros *et al*. (2020), Reddy *et al*. (2022), Quach *et al*. (2022), Suoniemi *et al*. (2020), and Walter *et al*. (2021) can guide discourse in this context. The proposed opportunities aim to elucidate (1) the relationships among different strategies (data, analytics, AI) and value creation; (2) organizational factors that hinder or facilitate strategic alignment; and (3) how data sharing, protection, and monetization strategies generate value. Additional questions address the impact of data-driven leadership and mindset on decision-making and the role of data literacy and individual strategic competencies in driving AI adoption, as discussed by Cezar & Maçada (2023), Fattah (2024), Huynh *et al*. (2025), and Javed & Akhlaq (2024).

The **fifth cluster**, encompassing business analytics intelligence, data science, and predictive analytics, shows a decline in prominence for certain topics. Nevertheless, the advent of AI integrated with analytic techniques brings forth emergent challenges that renew this research agenda, as begun by Bawack *et al*. (2022), Dubey *et al*. (2019b), Gunasekaran *et al*. (2017), Janssen *et al*. (2020), and Mikalef & Gupta (2021). The opportunities focus on how AI tools enhance descriptive, visualization, and predictive analyses for risk and opportunity anticipation, and on AI's impact in automating prescriptive analytics for optimization and innovation. A critical point is the *dark side* of data science and AI - algorithmic bias, privacy concerns, misinformation, overreliance - and its risks to organizational and competitive value creation.

In summary, we observe a flourishing trend of emerging organizational implications in bigdata and AI environments. There remains ample scope for meaningful theoretical contributions in analytics-capability research - particularly regarding data governance, data strategy, data management, and cultural/behavioral dimensions in data-driven organizations (leadership, analytical thinking, decision-making). Thus, this research agenda is essential for guiding future studies, providing clear directions for advancing knowledge in business strategy and information systems in the age of data and artificial intelligence.

4 Final Considerations

The aim of this conceptual study was to map the scientific literature addressing concepts related to D&A at the intersection of business strategy and information systems management. To achieve this, we conducted a bibliometric study with a sample of 1,229 publications, performing descriptive analyses, cluster analyses, and thematic mapping on a corpus of high quality, representative content.

Finally, the literature was organized, and the synthesis of perceived inferences enabled the systematization of a research agenda offering original questions to address theoretical gaps that may inspire future work and advance scientific knowledge on D&A and AI.

4.1 Theoretical Contributions

This study provides an overview of the literature over the past decade. The theoretical contributions are: (i) updating the state of knowledge; (ii) mapping scientific production; (iii) identification and analysis of co-citation and keyword clusters, with visual organization of predominant themes; and (iv) a research agenda to guide future advances.

First, this study updates, organizes, and expands the debate on organizational aspects of D&A holistically - filling a gap left by prior reviews focused on specific topics (e.g., business intelligence & analytics; BD; BDA; data science; data governance; data strategy & innovation; AI; data-driven culture). Uniquely, it adopts a broad scope centered on organizational factors and theories, systematically and visually presenting the state-of-the-art and research trends in D&A for business strategy and information systems management.

Second, mapping production and impact contributes to theory by highlighting the global relevance and influence of the topic - facilitating future researchers' identification of gaps. Key findings include: (i) an innovative and highly relevant theme (over 42,000 citations accumulated; H-index 98); (ii) the journals and research centers leading D&A research in the field; (iii) the most cited article directly addressing D&A (1,218 citations) and 15 articles with over 350 citations; and (v) global diffusion of research, led by European and North American centers, with significant contributions from China, India, Australia, and Brazil.

Third, cluster mappings (co-citation and thematic) pinpoint critical research focal points, current emphases, and existing gaps - helping scholars understand research topics and gain insights. The co-citation cluster map identified four clusters of the most important and influential publications forming the knowledge base (contextual, theoretical, methodological, thematic). The keyword cluster map, via link-strength analysis, uncovered five clusters classifying the knowledge domain. Thematic quadrants (motor, basic, emerging/declining, niche) further relate development level to relevance - facilitating comprehension and navigation of D&A knowledge.

Fourth, this study offers a suite of research opportunities. By addressing gaps and trends, future literature can advance concepts, perspectives, frameworks, methods, and objects of study. Especially given the proliferation of BDA and generative/agentic AI, describing new organizational and data-ecosystem characteristics under the umbrella of analytical, artificial, and digital transformation is - and will remain - an important emerging trend.

4.2 Practical Implications

The proposed mapping and debate support strategic alignment and analytical maturity assessment in organizations (Bisswang *et al.*, 2025; Grossman, 2018; Grover *et al.*, 2018; Medeiros, Maçada, & Freitas, 2021). A holistic view of D&A factors enables organizations to better manage strategy, resources, and capabilities to advance *data-driven* transformation (Aboelmaged & Mouakket, 2020; Al-Omoush *et al.*, 2024; Baecker *et al.*, 2025; Bhisikar, 2024; Côrte-Real, Oliveira, & Ruivo, 2019; Mazzei e Noble, 2017; Medeiros & Maçada, 2022). In sum, the learnings from this study serve researchers - offering insights into D&A literature gaps - and practitioners (e.g., CIOs, CDOs, CAOs) - providing a comprehensive understanding of D&A challenges, opportunities, and potential in organizational and business management.

4.3 Limitations

Although multiple angles and indicators were used to derive comprehensive and precise conclusions, we cannot guarantee that all results have been captured. Therefore, omissions or biases may exist in conclusions about critical research points and the evolution of D&A knowledge. Furthermore, while our chosen database (WoS) offers excellent coverage of current high-quality literature worldwide, some important studies may not have been included if they are not indexed there.

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