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Big Data Analytics in Organizational Process Management: A Systematic Review of Methods, Challenges, and Cultural Impacts

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Abstract. *Context: The adoption of Big Data Analytics (BDA) in organizational process management has been consolidated as a transformative strategy for organizations. The use of tools and methods based on advanced digital technologies supports decision-making more efficiently. Such practices generate benefits by optimizing managerial processes, increasing productivity, and enhancing strategic decisions. Problem: However, BDA implementation faces challenges such as the integration of large data volumes, privacy, ethics, and the lack of advanced analytical skills. In this sense, companies must invest both in technological infrastructure and in cultural changes. Objective: This paper analyzes how BDA have been applied in organizational process management and how they guide decision-making in the business context. Method: We conducted a systematic literature review, analyzing 176 empirical and theoretical studies published between 2019 and 2024 across five major databases. Results: The findings reveal a set of widely adopted methods and tools, including machine learning, BI/ERP systems, IoT, dashboards, and data mining frameworks, while also identifying recurrent barriers such as system integration issues, lack of analytical skills, and resistance to data-driven practices. The review highlights consistent impacts on organizational culture, including increased transparency, agility, and emphasis on evidence-based decision-making. Conclusions: The study contributes to the field by consolidating current knowledge on BDA in organizational processes, exposing research gaps, and offering insights to guide future implementations and investigations. By mapping practices, challenges, and impacts, this work supports researchers and practitioners in effectively integrating BDA to foster innovation, operational efficiency, and a robust data-driven culture.*

Keywords. *Big Data Analytics (BDA); management of organizational processes; decision-making; advanced digital technologies; corporate culture.*

1. Introduction

In recent years, organizational process management has undergone significant transformations due to the advancement of technologies and innovative methods, especially with the

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use of Big Data Analytics and decision support systems [Shafique et al. 2019]. Big Data Analytics refers to the process of collecting, processing, and analyzing large volumes of data to extract insights that can support strategic decision-making in organizations. This type of analysis is crucial for understanding complex patterns and trends that would be difficult to identify through traditional methods [Berges et al. 2021].

On the other hand, Decision Support Systems (DSS) are tools that assist in data analysis and decision-making through algorithms and models that process specific information. The main difference between them lies in the fact that Big Data Analytics focuses on large-scale data analysis, while DSS are directed toward specific decisions based on previously analyzed data. Thus, Big Data Analytics can be integrated into DSS to provide a broader and more strategic view, enhancing their effectiveness [Edelmann et al. 2023].

The integration of these technologies has allowed companies to optimize their operations, gain more accurate insights, and improve operational efficiency, generating competitive advantages in the market [Marquez-Chamorro et al. 2020]. With the increasingly complex business environment and the exponential growth of data, adopting advanced predictive analysis and process management strategies has become essential. These technological tools not only guide strategic decision-making but also promote continuous process optimization, contributing directly to the creation of competitive value [Edelmann et al. 2023].

The implementation of Big Data Analytics faces significant obstacles, such as the need to ensure data privacy and address ethical issues associated with the use of these technologies [Toshio et al. 2021]. Moreover, there is growing concern about the effective integration of these tools into existing organizational processes, which requires not only investment in infrastructure but also in training and cultural change within organizations [Rodríguez-Ibáñez et al. 2019].

The adoption of these technologies has led to significant changes in the way companies operate, promoting a culture more oriented toward data and less dependent on subjective intuitions. This transition to data-driven decision-making is transforming operational practices and redefining internal and external relationships within organizations, fostering a flexible and dynamic organizational culture that has proven crucial to meeting the challenges posed by digital transformation [Edelmann et al. 2023].

Despite the benefits of these technologies, there are challenges to be faced when implementing them, ranging from issues related to data privacy and security to difficulties in integrating new systems with existing infrastructures [Gangwar et al. 2023]. Thus, studying and integrating Big Data Analytics into organizational processes enables the generation of meaningful insights that improve decision-making processes. These insights provide a deeper understanding of the market, allowing the development of more efficient strategies for organizational process management [Mariani and Nambisan 2021]. In addition to promoting efficiency and innovation, this approach also contributes to creating an adaptable work environment with a data-driven culture prepared for the future [Alaskar 2023].

Although the use of Big Data Analytics in organizational processes has grown in

recent years, there is a lack of integrated syntheses explaining how these technologies effectively support decision-making within process management. Moreover, the challenges organizations face, such as system integration, analytical skill gaps, and cultural resistance, appear in a superficial manner, making it difficult to understand what truly enables or hinders BDA adoption. Another relevant gap concerns the limited consolidation of knowledge on how BDA transforms organizational culture, a topic that is increasingly discussed but still underexplored.

Given these gaps, the objective of this work is to develop an analysis of the definition, importance, methods, tools, challenges, impacts, and processes related to the use of Big Data Analytics in organizational process management, based on studies and published articles addressing these points. To achieve this objective, a systematic literature review was conducted regarding this context, enabling an evaluation of the results obtained from the selected studies.

The main guiding question of the research is: *What is the state of the art in research involving Big Data Analytics in the context of decision-making in organizational processes?*

The research questions were formulated to address three essential and insufficiently investigated dimensions: (i) the methods and tools currently applied in practice (RQ1), (ii) the challenges encountered and the strategies used to overcome them (RQ2), and (iii) the impacts of BDA on organizational culture and decision-making (RQ3).

Although previous literature reviews have examined Big Data Analytics from technological or managerial perspectives, most of them focus on isolated aspects, such as analytical capabilities, performance outcomes, or specific sectors, and do not integrate the different dimensions involved in the use of BDA within organizational process management. In contrast, the contribution of this study lies in offering a comprehensive synthesis that connects methods and tools, implementation challenges, and cultural and behavioral impacts, dimensions that prior reviews rarely analyze together. Furthermore, by incorporating studies published between 2019 and 2024 across five major databases, this review provides an updated and broader view of the field, highlighting trends that emerged only in the most recent literature, such as the growing relevance of data-driven culture, the interplay between BDA and organizational capabilities, and the operational implications of digital transformation. As a result, this study not only consolidates what is known but also clarifies gaps, tensions, and emerging patterns that have not been systematically addressed in earlier reviews, offering researchers and practitioners a more integrated and actionable understanding of how BDA supports decision-making in process management.

This work is organized into five sections. Section 2 discusses background and related works. Section 3 describes the research method. Section 4 highlights the results obtained from the research. Finally, Section 5 provides conclusions and future works.

2. Background

2.1. Big Data Analytics

Big Data Analytics (BDA) refers to the process of analyzing large volumes of data to discover hidden patterns, unknown correlations, market trends, customer preferences,

or other useful information, depending on the business and objective, allowing organizations to extract significant insights that improve their decision-making processes [Edelmann et al. 2023]. BDA is fundamental in the digital era, as it enables organizations to use real-time data to develop strategies, providing a significant competitive advantage. In this context, organizations are leveraging various advanced tools and methods, such as machine learning, artificial intelligence, predictive analytics, and statistical techniques, to guide strategic planning, improve operational efficiency, and forecast future trends [Berges et al. 2021].

The BDA process follows several phases. The first is data collection, which encompasses both structured and unstructured data, such as images and videos. Next, the data preparation phase ensures cleaning and transformation of the data for subsequent analysis [Rodríguez-Ibáñez et al. 2019]. After preparation, the data undergoes analysis, involving the application of machine learning algorithms and statistical techniques to identify patterns. Finally, the insights are visualized in charts or reports to facilitate interpretation by decision-makers, who, based on these insights, implement improvements and adjusted strategies [Marquez-Chamorro et al. 2020].

In this context, the analysis of large volumes of data, when applying BDA in organizational process management, allows inefficiencies to be identified and improvements to be implemented proactively, increasing operational efficiency and reducing costs, resulting in more agile and effective operations [Aguilar-Chávez et al. 2021]. The ability to analyze complex data allows organizations to identify emerging trends, anticipate market changes, and develop strategies based on solid evidence. This not only improves decision-making but also aligns business operations with long-term strategic objectives [Toshio et al. 2021].

The integration of BDA promotes a significant shift in organizational culture, where decisions are based on accurate analyses rather than intuitions or assumptions. This transformation is reshaping how organizations operate, fostering a culture of continuous innovation and adaptability. By adopting a data-driven mindset, companies not only improve efficiency but also strengthen their capacity to innovate and adapt to market changes [Shi An et al. 2021].

2.2. Organizational Process Management: Decision-Making, Management, and Data Culture

Organizational process management involves the efficient coordination of a company's internal activities to improve its performance and achieve its strategic goals [Jonny et al. 2021]. One of the main components of process management is decision-making, which plays a central role in all operational and strategic stages. Nowadays, this process has become more complex and strategic, especially with the growing need to integrate data-driven decisions and the use of advanced technologies to improve organizational performance [Edelmann et al. 2023].

The inclusion of large volumes of data in decision-making for process management offers a unique ability to predict outcomes and adjust operations in real time, providing a competitive edge [Marquez-Chamorro et al. 2020]. The ability to store, process,

and interpret such data is essential for operational effectiveness, ranging from supply chain optimization to enhancing customer experience [Jonny et al. 2021].

Moreover, the creation of a data-driven culture is essential to consolidate these practices, going beyond the use of tools and involving an organizational shift that encourages all levels of the company to make decisions based on data rather than relying solely on intuition or past experience. In this context, companies that adopt this mindset observe significant impacts on their operations, as a data-oriented culture promotes more agile and flexible management, helping organizations adapt better to market changes and make more informed decisions [Rodríguez-Ibáñez et al. 2019].

Thus, modern organizational process management encompasses not only internal efficiency but also the ability to integrate data and technology into decision-making processes. The combination of data-driven decision-making, efficient information management, and an organizational culture that values these elements enables companies to remain competitive in an increasingly innovation-oriented and data-driven business environment.

3. Method

This section presents a systematic literature review protocol using the approach defined by[Kitchenham and Charters 2007]. The process carried out is described in the following subsections.

3.1. Research Questions

This work is guided by the following research questions (RQ):

- **RQ1:** What methods and tools are organizations currently using to guide decision-making in organizational process management, and how are these strategies generating benefits? Without a consolidated mapping of methods, organizations cannot identify which technologies are most compatible with their maturity level, nor can they understand the actual benefits reported in prior research. For the reader, RQ1 clarifies which tools truly contribute to process efficiency, how they are being deployed, and what operational advantages were empirically observed.
- **RQ2:** What are the main challenges faced by organizations when implementing and using Big Data Analytics in organizational process management, and what strategies are being employed to overcome them? By addressing RQ2, this review makes explicit the organizational implications of technical and cultural barriers, enabling practitioners to anticipate bottlenecks and evaluate whether their internal conditions resemble those documented in the literature. The results also provide researchers with a clearer view of unresolved or emerging challenges that require deeper investigation.
- **RQ3:** What are the potential impacts observed from the use of Big Data Analytics on organizational culture, and how are these changes influencing the way organizations operate? Cultural resistance is often cited as a barrier, yet few studies explain how BDA adoption modifies employee behavior, what competences become critical, or how cultural evolution interacts with technological maturity.

RQ3 addresses this dispersion by systematizing the cultural transformations observed across empirical contexts. The impacts synthesized here help the reader understand what organizations actually gain or lose culturally, and what types of behavioral change are necessary for BDA to produce results.

3.2. Databases and Search String

The following search string was defined:

("big data analytics" OR "big data" OR "organizational intelligence" OR "business intelligence") AND ("business process management" OR "business processes" OR "organizational processes" OR "operations management") AND ("decision making" OR "predictive analytics" OR "predictive analysis" OR "organizational strategies") AND ("data management" OR "data administration" OR "data science" OR "data analysis") AND ("knowledge oriented" OR "data driven culture" OR "organizational knowledge" OR "data culture")

With this search string, it was possible to perform the query in five databases: IEEE, ACM, Science Direct, Scopus, and Springer.

3.3. Inclusion and Exclusion Criteria

The exclusion criteria used to select the papers were:

- **EC01** – Articles not within the period 2019 to 2024
- **EC02** – Secondary articles (other SLR or SMS)
- **EC03** – Articles unavailable for download or viewing
- **EC04** – Duplicate or similar articles
- **EC05** – Articles not related to the research questions
- **EC06** – Articles not written in English or Portuguese
- **EC07** – Articles with fewer than 4 pages
- **EC08** – Articles with more than 30 pages

3.4. Article Selection

The initial search retrieved 772 studies across the five databases, and the application of exclusion criteria substantially reduced this number, as summarized in Table 1. Titles and abstracts were then screened to ensure alignment with the research scope, eliminating works unrelated to Big Data Analytics, decision-making, or organizational process management.

Since the first filtering stage did not assess the methodological or conceptual quality of the papers, a second qualification step was conducted through a focused reading of introductions, conclusions, and key sections. Articles were evaluated using five quality criteria—context clarity, methodological soundness, explicit model or proposal, practical application, and relevance of the discussion, each scored from 0 to 1. Only studies scoring at least 3.5 (70%) and meeting the last two criteria were retained. As shown in Table 1, this qualification stage further reduced the corpus, resulting in a final set of 176 selected articles.

Table 1. Reduction of articles during the screening and qualification stages

Database	Initial Search	After Exclusion	After Qualification
Scopus	437	109	96
IEEE Xplore	171	28	12
ScienceDirect	74	55	50
Springer	55	19	17
ACM Digital Lib.	35	2	1
Total	772	213	176

3.5. Overview of selected studies

After analyzing the selected articles, a mapping of the studies by year of publication was carried out. By grouping the studies by period, it was possible to confirm the growing relevance of the topic of Big Data Analytics in recent years. As this context continues to gain importance in society, it is expected that the number of publications related to the theme will gradually increase.

With the aim of identifying which database contained the highest concentration of studies, a mapping of the publications was carried out by source in order to determine each database's contribution to the theme. The database with the largest number of published articles was Scopus, followed by Science Direct, Springer, IEEE, and ACM. The selected papers are listed in Table 3.5.

3.6. Limitations and Threats

For the execution of this work, five different databases were used (ACM, Springer, IEEE, Science Direct, and Scopus). However, only studies with free or institutional access were considered, which may have limited the scope of the research by excluding paid and potentially relevant studies. This limitation affects construct validity, since the selection of studies was influenced by access availability, which may have resulted in an incomplete view of the literature.

In addition, only articles written in English or Portuguese were analyzed, which may have excluded relevant studies published in other languages. This restriction can be considered a threat to external validity, as the results may not be generalizable to studies in other languages that could contain valuable insights.

Finally, it is important to highlight that although this work includes studies from 2024, it is limited to those published only within the first four months of the year. This restricts the temporal scope of the analysis, representing a threat to internal validity, since the limited time frame may not capture significant trends or findings published later in the year.

4. Results

This chapter is divided into three sections and presents the results for the research questions defined in the objectives of this work. The first section presents the findings related to Research Question RQ1, the second addresses Research Question RQ2, and the third discusses Research Question RQ3.

Table 2. Selected papers

Ano	Artigos
2019	A2[Shafique et al. 2019], A3[Rodríguez-Ibáñez et al. 2019], A14[Nam et al. 2019], A15[Božič and Dimovski 2019a], A16[Dubey et al. 2019b], A17[Shamim et al. 2019], A18[Côrte-Real et al. 2019], A65[Dubey et al. 2019a], A66[Božič and Dimovski 2019b], A67[Abueed and Aga 2019], A68[Chierici et al. 2019], A160[Obitade 2019], A161[Sleep et al. 2019]
2020	A4[Marquez-Chamorro et al. 2020], A19[Gupta et al. 2020], A20[Dremel et al. 2020], A21[Hallikainen et al. 2020], A22[Troisi et al. 2020], A23[Upadhyay and Kumar 2020], A24[Hausladen and Schosser 2020], A25[Duan et al. 2020], A26[Farrokhi et al. 2020], A30[Ashaari et al. 2021], A70[Maroufkhani et al. 2020], A71[Dubey et al. 2020], A72[Mariani and Wamba 2020], A73[Zhang et al. 2020], A74[Wamba et al. 2020], A162[Fosso Wamba et al. 2020], A163[Bertello et al. 2020], A164[Kumar and Krishnamoorthy 2020], A165[Gökalp et al. 2020]
2021	A5[Toshio et al. 2021], A6[Berges et al. 2021], A7[Aguilar-Chávez et al. 2021], A8[Jonny et al. 2021], A9[Shi An et al. 2021], A10[Budeanu and Rosner 2021], A27[Zhu et al. 2021], A28[Neirotti et al. 2021], A29[Raut et al. 2021], A31[Ranjan and Foropon 2021], A32[Shamim et al. 2021], A33[Kim et al. 2021], A34[Ciampi et al. 2021], A35[Sjödin et al. 2021], A36[Rukanova et al. 2021], A37[Mariani and Nambisan 2021], A38[Yu et al. 2021], A39[Kozak et al. 2021], A40[AlNuaimi et al. 2021], A75[Öhman et al. 2021], A76[Chatterjee et al. 2021], A77[Bag et al. 2021a], A78[Awan et al. 2021], A79[Sundarakani et al. 2021], A80[Eslami et al. 2024], A81[Han et al. 2024], A83[Singh et al. 2021], A84[Bag et al. 2021b], A85[Ali et al. 2021], A86[Hajli et al. 2021], A87[Hossain et al. 2021]
2022	A11[Perea and Festijo 2022], A41[Ashrafi and Zareravasan 2022], A42[Wei and Pardo 2022], A43[Chen et al. 2022b], A44[Perdana et al. 2022], A45[Kayabay et al. 2022], A46[Liang et al. 2022], A47[Elia et al. 2022], A48[Zhang et al. 2022], A88[Chowdhury et al. 2022], A89[Rodríguez-Espíndola et al. 2022], A90[Fernandes et al. 2022], A91[Bag et al. 2022a], A92[Adam et al. 2022], A93[Dwivedi et al. 2022], A94[Chatterjee et al. 2024b], A95[Gupta et al. 2022], A96[Sultana et al. 2022], A97[Uddin Murad et al. 2022], A98[Boccali et al. 2022], A99[Chen et al. 2022a], A100[Horng et al. 2022], A101[Zieba et al. 2022], A102[Bag et al. 2022b], A103[Al-Okaily 2024], A167[Gao and Sarwar 2022], A168[Li and Kettinger 2022]
2023	A1[Edelmann et al. 2023], A12[Jayashree et al. 2023], A49[Sjödin et al. 2023], A50[Corallo et al. 2023], A51[Abadie et al. 2023], A52[Gallego-García et al. 2023], A53[Rahman et al. 2023], A54[Morimura and Sakagawa 2023], A55[Zhu and Li 2023], A56[Fareri et al. 2023], A57[Li and Griffin 2023], A106[Chatterjee et al. 2023c], A107[Gangwar et al. 2023], A108[Olan et al. 2024], A109[Waheed et al. 2023], A110[Chatterjee et al. 2023b], A111[Lee and Kim 2023], A112[Garmaki et al. 2023], A113[Mao and Lu 2023], A114[Zheng et al. 2023], A115[ZareRavasan 2023], A116[Hautala-Kankaanpää 2023], A117[Tseng 2023], A118[Kakhki et al. 2022], A119[Hossain et al. 2023], A120[Fattah and Arief 2023], A121[Chatterjee et al. 2023a], A122[Cadden et al. 2023], A123[Dirnberger et al. 2023], A124[Lee et al. 2024], A125[Qiao et al. 2023], A126[Touil and Jabraoui 2023], A129[Hijazin et al. 2023], A130[Bacon et al. 2023], A131[Makhloufi 2024], A132[Klein et al. 2023], A133[Widtayakornbundit and Luangpituksa 2023], A134[Kalbouneh et al. 2023], A135[Al-Okaily et al. 2023], A136[Cheng et al. 2023], A137[Abuzaid et al. 2023], A138[Kadarsah et al. 2023], A139[Wang et al. 2023], A140[Makhloufi et al. 2023], A141[Marjanovic et al. 2023], A170[Bayraktar et al. 2023], A171[Malacaria et al. 2023], A172[Weber et al. 2023]
2024	A13[Persaud and Zare 2023], A143[Alghamdi and Agag 2024], A144[Ozdemir et al. 2024], A145[Kava et al. 2024], A146[Chatterjee et al. 2024a], A147[Babu et al. 2024], A148[Bhatti et al. 2024], A149[Jackson et al. 2024], A150[Korayim et al. 2024], A151[Liébana-Cabanillas et al. 2024], A152[Chatterjee and Chaudhuri 2024], A153[Hossain et al. 2024], A154[Culot et al. 2024], A155[Mbaidin 2024], A156[Dubey et al. 2024], A157[Wamba et al. 2024], A158[Agag et al. 2024], A159[Fayyaz et al. 2025], A166[Karaboga et al. 2022], A173[Haverila et al. 2024], A174[Min and Lea 2024], A175[Alaskar 2024], A176[Wong and Ngai 2024]

4.1. RQ1: Methods and Tools to Guide Decision-Making in Organizations

The first research question of this study seeks to understand the methods and tools that organizations use to guide decision-making in the management of organizational processes. The table 3 presents the tools, methods, and methodologies identified in the selected articles.

Table 3. List of tools, methods, and methodologies.

Method/Tool	Number of Articles Mentioning These Techniques	Main Articles
Big Data Tools: HDFS, HBase, Kafka, Spark	7	A34, A50, A77, A79, A95, A139, A147
Internet of Things (IoT)	8	A5, A56, A59, A61, A80, A85, A88, A125
Business Intelligence (BI) and ERP	20	A10, A53, A62, A63, A69, A76, A79, A86, A93, A105, A106, A114, A130, A135, A137, A148, A153, A154, A160, A169
BI Tools: Google Sheets, Excel, MySQL, etc.	6	A34, A44, A102, A123, A145, A161
AI Tools: Opinion Crawl, Semantria, R, Python, etc.	7	A41, A44, A54, A86, A120, A145, A149
AI-based CRM Tools: Demandbase, HubSpot, Salesforce Einstein	5	A21, A53, A76, A123, A153
Blockchain	6	A10, A56, A59, A89, A90, A114
Machine Learning	19	A10, A11, A13, A26, A28, A39, A43, A45, A94, A96, A102, A137, A143, A144, A150, A157, A161, A173, A176
Process Automation	5	A5, A48, A44, A106, A123
Interactive Dashboards	10	A6, A35, A41, A82, A135, A138, A145, A155, A162, A169
Green Lean Six Sigma (GLSS), Sustainable Supply Chain Management (SSCM)	10	A48, A79, A91, A102, A116, A118, A121, A128, A150, A159
OLAP Cubes	3	A6, A135, A155
Data-Driven Innovation (DDI)	23	A14, A15, A34, A36, A73, A77, A81, A87, A90, A91, A96, A101, A112, A116, A120, A122, A125, A143, A160, A162, A163, A164, A176
ORGANON, KDD, OSEMN, TDSP	1	A45
Cross-Industry Standard Process for Data Mining (CRISP-DM)	15	A10, A30, A35, A45, A46, A59, A60, A62, A147, A148, A154, A157, A161, A172, A174
Multi-Criteria Decision-Making (MCDM) & DEMATEL	3	A97, A107, A171
Fuzzy Analytic Hierarchy Process (FAHP)	1	A108
Maturity Models (MMs)	5	A24, A51, A126, A138, A171
Development of Human Skills and Team Training for BDA Use	19	A13, A18, A19, A27, A33, A34, A37, A39, A44, A47, A56, A65, A83, A88, A106, A107, A128, A140, A157

Big Data Analytics (BDA) enables the discovery of hidden patterns in large volumes of data, generating valuable insights for organizations. These insights provide a deeper understanding of the market, enhancing business intelligence by offering a detailed view of competitors, customers, suppliers, and other stakeholders. In this way, companies can develop strategies that maximize customer satisfaction and manage risks in the supply chain more efficiently [Mariani and Nambisan 2021]. To make such analysis effective, tools such as HDFS, HBase, Kafka, and Spark are widely used [Corallo et al. 2023].

The implementation of Big Data Analytics Capabilities (BDACs) is essential to maximize the benefits of BDA. BDACs encompass tangible resources (data, technology, investment), human resources (managerial and technical skills), and intangible resources (data-driven culture and organizational learning). These resources allow organi-

zations to deploy technology and talent effectively to capture, store, and analyze data, improving both organizational performance and agility ([Mariani and Nambisan 2021]. A clear example is the integration of the Internet of Things (IoT) with Big Data Analytics, which enables real-time data collection and analysis, significantly improving business processes and routine activities [A5]. As a result, decisions become faster and more effective, supporting market-aligned strategies, boosting productivity, and reducing costs [Toshio et al. 2021].

In parallel, Business Intelligence (BI) and Enterprise Resource Planning (ERP) systems make it possible to monitor and generate real-time reports, integrating information flows necessary for effective management control at different organizational levels [A62]. These systems provide a comprehensive and detailed view of organizational performance through Key Performance Indicators (KPIs), supporting better strategic planning and operational management [A62]. Among the main tools used are Google Sheets, Microsoft Excel, MySQL, Microsoft Access, SQL Server, PostgreSQL, Tableau, Qlik Sense, Microsoft Power BI, and Microstrategy—all essential for managing and visualizing data in various operational domains such as accounting, finance, and human resources [A44].

Artificial Intelligence (AI) also plays a crucial role in supporting more informed and effective decision-making, particularly in risk management contexts. When integrated with data mining, AI processes and learns from data, offering analytical capabilities to understand the impact of risks, provide automated recommendations, react quickly to changes, and identify trends. This facilitates efficient resource allocation and strengthens decision-making during crises [A89]. Tools such as Opinion Crawl, Semantria, R, Python, Alteryx Designer, RapidMiner, Orange, SAS, KNIME, MS Azure Machine Learning Studio, and BigML are frequently employed for complex analyses, including customer feedback and process automation [A44].

AI-based Customer Relationship Management (CRM) tools, such as Demandbase, Terminus, HubSpot, and Salesforce Einstein, have also been increasingly applied. These platforms integrate predictive analytics and machine learning, improving customer relationship performance and contributing to more sustainable social outcomes [A53].

Another significant technological advance is the use of blockchain, which enables traceability and monitoring of information, secure transactions, and improved data quality and reliability. This results in faster decisions and more effective communication with customers and suppliers, supporting risk management [A89]. Complementarily, machine learning optimizes processes by predicting outcomes based on historical data, offering competitive advantages through more timely and evidence-based decisions [A28].

Process automation has become a vital tool in modernizing organizational operations, reducing the time required for routine tasks and allowing employees to focus on more strategic activities. This not only increases productivity but also improves work quality by reducing the incidence of human errors [A112]. Supporting these innovations, data visualization tools have become indispensable, facilitating the interpretation of large volumes of information and making the decision-making process more intuitive and accurate [A82]. Interactive dashboards, for instance, are widely used to monitor real-

time performance, helping quickly identify problems and opportunities for improvement [A38].

This integration of technologies and techniques goes beyond traditional database management systems, incorporating Big Data processing tools that handle structured, semi-structured, and unstructured data. This helps reveal meaningful insights from large data sets, improving decision-making processes [A30]. Consequently, organizations are carefully investing in and planning Big Data initiatives, coordinating across departments and creating control mechanisms to maximize Big Data Analytics in decision-making and infrastructure development [A30]

For effective BDA implementation, methodologies such as Green Lean Six Sigma (GLSS) and Sustainable Supply Chain Management (SSCM) are increasingly applied. GLSS integrates lean principles with environmental initiatives, helping organizations comply with regulations, achieve sustainability goals, and improve economic performance. SSCM promotes sustainability in the supply chain by reducing waste and environmental impacts, while also ensuring timely product delivery and improved stakeholder working conditions [A159]. Another relevant method is the use of OLAP cubes, which allow dynamic data analysis, enabling managers to explore associations as needed, particularly useful in predictive analysis and data mining projects [A6].

Methodologies such as Data-Driven Innovation (DDI) and ORGANON are also applied to optimize processes and develop new business models based on large-scale data analysis [A176]. Knowledge Discovery in Databases (KDD) and the Cross-Industry Standard Process for Data Mining (CRISP-DM) also play fundamental roles by structuring data analysis through sequential phases, such as understanding the data and modeling [A45]. ORGANON, for instance, focuses on identifying contextual information that influences organizational process performance, including external conditions, human factors, or operational variations. Its application involves interviews and the collection of information from process analysts to identify significant contextual factors, which are then integrated into predictive models, helping organizations perform more accurate and informative monitoring of their processes [A4].

Other approaches, such as OSEMN (Obtain, Clean, Explore, Model, Interpret) and Team Data Science Process (TDSP), provide additional frameworks for structuring data science projects [A45]. Multi-Criteria Decision-Making (MCDM) techniques, specifically the DEMATEL (Decision-Making Trial and Evaluation Laboratory) method, are applied to analyze complex decision-making scenarios, mapping relationships and influences among multiple factors.

Among decision-making methods, the Fuzzy Analytic Hierarchy Process (FAHP) is noteworthy. It integrates fuzzy set theory with the Analytic Hierarchy Process (AHP) to address uncertainty, ambiguity, and vagueness in human decision-making. The goal of FAHP is to quantitatively weigh variables through user interaction with mathematical models while also allowing qualitative flexibility, enabling decision-makers to express preferences more effectively [A107].

Finally, the use of maturity models (MMs) provides a structured strategy for as-

sessing and improving organizational capabilities. These models enable companies to align processes effectively and reach higher levels of maturity by identifying areas for improvement [A24]. Furthermore, the development of human skills is crucial for the proper use of Big Data Analytics, requiring the training of managers and technical teams to coordinate and maximize data pipelines and design algorithms that enhance organizational outcomes (Ciampi et al., 2021).

In summary, the study explores the tools and methods used by organizations in decision-making, with an emphasis on Big Data Analytics (BDA) and its Capabilities (BDACs). BDA enables the discovery of hidden patterns in large data sets, generating valuable insights for business intelligence, positively impacting risk management, competition, customers, and the supply chain. Tools such as HDFS, Spark, and Kafka, combined with BDACs that integrate technological, human, and cultural resources, drive these benefits. IoT and machine learning enhance real-time processes, while BI and ERP systems integrate information for managerial control. AI and AI-based CRM tools optimize decision-making and customer relations. Blockchain supports secure transactions and traceability, while process automation improves efficiency. Data visualization with interactive dashboards makes decision-making more precise.
Moreover, methodologies such as GLSS and SSCM foster sustainability and organizational performance. Data mining methodologies like CRISP-DM and KDD structure data analysis, while FAHP supports decision-making in complex and uncertain scenarios. Maturity models assess and enhance organizational capabilities, and the development of human skills and team training is essential to maximize the use of BDA.

4.2. RQ2: Main challenges faced by organizations when implementing and using Big Data Analytics in organizational process management

The second research question highlights the challenges in implementing and using Big Data Analytics for decision-making in the organizational environment and the strategies adopted to overcome these barriers. The table 4 presents the challenges found and the strategies proposed to address them.

The main challenges faced by organizations when implementing and using BDA in organizational process management include the complexity and rigidity of existing data systems. Traditional processes of obtaining data for decision-making are slow and error-prone, involving multiple steps and requiring validation from different management units [A6]. In addition, integration issues frequently arise as obstacles, since combining different systems and data sources may compromise the quality of analyses (Berges et al., 2021).

Another relevant factor is the complexity of data processing, which demands significant investments in management capacity and infrastructure. This requires aligning these capabilities with the organization's strategic objectives while handling large volumes of data [A142]. This scenario is particularly challenging for small and medium-sized enterprises (SMEs), which, due to limited resources, often face difficulties in

Table 4. List of challenges and strategies.

Challenge	Mitigation Strategy	Main Reference
Complexity and rigidity of existing data systems	Creation of stable and flexible data structures	A6
Integration of different systems and data sources	Involvement of organizational members from the beginning of the process	A6
Complexity of data processing	Adoption of strategic intelligence systems and cloud-based solutions	A142
Lack of adequate support for risk management	Align BDA knowledge with risk management practices	A127
Enhancing marketing analytics capability (MAC)	Integrated approach to resources and capabilities	A142
Maintaining visibility in supply chains	Develop a robust technological infrastructure	A77
Lack of human and technological capabilities in BDA	Development of an analytical culture and training programs	A13
Resistance from non-technical professionals	Training programs and strategic partnerships	A13
Concerns with privacy, ethical dilemmas, and data leakage	Adoption of Privacy by Design (PbD) frameworks and robust access and identity management systems	A86

smoothly integrating big data analytics into their processes (Abrokwah-Larbi, 2024).

To overcome these challenges, organizations are adopting strategic intelligence systems that provide more accurate and real-time knowledge of their operations. This involves creating stable and flexible data structures that allow exploratory data analysis without disrupting daily operations [A6]. The involvement of organizational members from the beginning of the process is essential to ensure that platforms are aligned with internal needs, increasing acceptance and functionality (Berges et al., 2021). These advances require robust investments in infrastructure and technology to handle large data volumes and secure adequate funding to achieve strategic goals through BDA [A34]. Cloud-based solutions have proven to be effective strategies, offering scalability and cost efficiency for data processing and analysis. Advanced visualization tools and parallel computing approaches are also being implemented to enhance analytical efficiency [A34].

Additionally, the lack of adequate support for risk management is a significant obstacle, particularly in high-risk environments that depend on Business Intelligence (BI) analyses to identify new opportunities and risks. Although risk management is widely recognized as a critical factor for organizational success, many companies still fail to perceive a clear correlation between risk management capabilities and the success of BI initiatives [A127]. Aligning BDA knowledge with risk management practices can improve both agility and organizational performance [A175].

Within the organizational context, enhancing marketing analytics capability (MAC) has been identified as crucial for companies to convert marketing efforts into competitive advantage [A142]. This requires an integrated approach to resources and capabilities, aligning MAC with organizational structures and strategic objectives, which is fundamental to overcoming the challenges inherent in implementing BDA [A142].

It is also essential to develop robust technological infrastructures to ensure data quality, speed, and reliability, enabling efficient information exchange [A77]. This is particularly important for maintaining visibility in supply chains, where timely and accurate information exchange is vital [A77]. However, organizational challenges such as

the lack of human and technological capabilities in BDA and the need to build a strong analytical culture often hinder the adoption of data-driven decision-making at all levels [A13]. Moreover, resistance among non-technical professionals to adopt unfamiliar tools, compounded by a lack of top management support—especially when innovations demand significant changes to existing processes—further complicates the situation [A60].

To mitigate these problems, many organizations are investing in the development of an analytical culture, fostering data-driven decision-making and improving their absorptive capacity [A13]. Training programs to qualify employees, along with strategic partnerships with external technology providers, are strategies adopted to overcome these obstacles [A13].

In the use of AI and BDA, organizations must invest in developing three essential entrepreneurial characteristics: proactiveness, risk-taking, and innovativeness. The integration of these capabilities with BDA and AI is strategically justified in many organizational contexts. Managers with entrepreneurial orientation are able to build and exploit these dynamic capabilities, achieving sustainable competitive advantage [A71]. It is crucial for managers to understand where and how to implement and leverage these technologies, since developing effective routines can be gradual and requires patience [A16].

There are also growing concerns regarding privacy, ethical dilemmas, and data leakage when using BDA. Privacy and data security issues are critical, as they can prevent organizations from achieving desired performance and competitive advantage [A86]. To mitigate these risks, many companies are adopting Privacy by Design (PbD) frameworks within Enterprise Architecture (EA), redesigning online user interfaces to proactively protect private information [A86]. They are also aligning IT strategies with business strategies and employing methodologies that integrate privacy and security considerations into their EA models [A107]. Adapting to new operational flows introduced by BDA requires substantial change management capabilities, as well as the implementation of robust access and identity management systems to prevent unauthorized access and adopting effective cryptographic solutions for data security [A107].

The need for data confidentiality demands the implementation of formal protection mechanisms such as contracts, intellectual property rights, and information security standards, which define how data may be used and shared [A154]. These mechanisms help build trust among partners and encourage the secure exchange of information [A154].

In summary, the implementation of Big Data Analytics (BDA) in organizations faces multiple challenges, such as the complexity of existing data systems, integration difficulties, and the need to align data processing capabilities with strategic business objectives. SMEs face additional barriers due to resource constraints, while internal resistance, especially from non-technical professionals, and lack of top management support further complicate adoption. To mitigate these challenges, companies have invested in robust technological infrastructure—such as cloud solutions, parallel computing, and visualization tools—while promoting an analytical

culture that values data-driven decision-making. Training programs and partnerships with technology providers also help prepare organizations to handle large data volumes and improve operational efficiency.
Furthermore, privacy and data security issues remain critical, requiring organizations to adopt strategies such as Privacy by Design (PbD) and robust security frameworks. These strategies not only protect sensitive data but also encourage the secure exchange of information among partners. Risk management remains essential, especially in dynamic environments, and requires aligning BDA capabilities with risk management practices. The combination of entrepreneurial orientation, investments in innovation, and the strategic use of AI and BDA enables companies to build dynamic capabilities, develop competitive advantage, and enhance decision-making in an increasingly data-driven environment.

4.3. RQ3: The potential impacts observed from the use of Big Data Analytics on organizational culture

This section aims to demonstrate the impacts observed in the use of BDA, analyzing how these changes influence the way organizations operate. The table 5 presents the data and impacts of Big Data Analytics (BDA) on organizational culture.

The promotion of a data-driven culture forces organizations to adopt a more informed and precise approach to decision-making [A5]. This is evident in companies transitioning from intuition- and experience-based decisions to choices grounded in insights derived from the analysis of large volumes of data [A5]. Access to real-time data, combined with advanced analytical tools, allows managers to make better-informed decisions with greater agility, reducing the need for lengthy reporting processes. Furthermore, consolidating data from different systems into a single platform promotes greater collaboration and integration across management units. This not only optimizes operations but also strengthens a culture of shared responsibility and continuous improvement [A6]. The adoption of a strategic intelligence approach ensures that changes in organizational status are automatically reflected, reducing the need for constant manual adjustments and enabling more flexible and comprehensive analyses [A6].

With the integration of Big Data Analytics (BDA), organizations not only foster transparency and accountability but also improve evidence-based management. BDA enhances agility and resilience in operations, enabling rapid adaptation to market changes and more effective risk management [A29]. Through its adoption, companies can also implement lean and sustainable practices in the supply chain, reinforcing both sustainability and operational efficiency. Moreover, this adoption requires organizations to develop and cultivate advanced technical skills within their workforce, fostering a culture of continuous learning and innovation. These cultural shifts extend beyond operational performance, positioning companies to better respond to market dynamics and achieve long-term strategic goals [A29].

However, this transformation also demands constant focus on learning and adaptation, as organizations must regularly update their tools and analytical techniques to keep pace with evolving threats and market conditions [A160]. The use of BDA increases

Table 5. List of BDA impacts on organizational culture.

BDA Aspect	Impact on Organizational Culture	Main Reference
Data-driven culture	The adoption of a data-driven culture transforms the way decisions are made, fostering a more objective and analytical mindset across the organization. Teams rely less on intuition and more on concrete evidence.	A5
Real-time access and advanced tools	Quick access to information improves organizational agility. It encourages a culture of rapid response and proactivity, reducing bureaucracy and enhancing team alignment.	A5
Data consolidation	The integration of different units through data consolidation strengthens collaboration across departments, reducing organizational silos. This fosters a culture of knowledge sharing and greater cooperation.	A6
Strategic intelligence	Rapid and automatic changes in strategy can create a more adaptive and flexible culture, where everyone must be prepared to adjust plans and processes as data reveals new opportunities or risks.	A6
Transparency and evidence-based management	Transparency increases internal trust and may establish a culture where each decision is visible and justified by data, promoting greater responsibility and clarity.	A29
Skill development	With the implementation of BDA, employees need to acquire new technical skills, fostering a culture of continuous learning and specialization. This may generate an environment of constant updating and pursuit of new knowledge.	A29
Continuous learning and adaptation	Continuous learning becomes a central value, encouraging an open mindset toward change and adaptability. Organizational culture becomes more dynamic and less resistant to technological transformations.	A160
Response to cyber threats	The growing concern with cybersecurity means that company culture becomes more oriented toward data protection and risk management. This fosters a more cautious and conscious stance toward the use and sharing of information.	A160
Development of new capabilities	The need to develop new technical and analytical capabilities fosters a culture of innovation and pursuit of efficiency. This encourages employees to step out of their comfort zones and seek creative solutions to complex problems.	A36
Stakeholder alignment	BDA improves communication and alignment with stakeholders, making the organization more transparent and collaborative. This fosters a culture focused on stakeholder satisfaction and encourages active participation in decision-making.	A147
Complexities of BDA integration	The integration of BDA may reveal technical and cultural challenges, such as the need to change processes and mindsets. This requires a resilient and flexible culture capable of managing complexity and overcoming obstacles during digital transformation.	A33
Employee resistance	Resistance may arise when employees face new technologies. This can create a culture of mistrust or fear of change, which must be addressed through clear communication, proper training, and continuous support to ensure adoption.	A60
Promotion of a data-driven culture	The active promotion of a data-driven culture strengthens the use of metrics and analytics at all levels of the organization. This reduces reliance on intuition and emphasizes decision-making based on concrete and measurable information.	A14
Incentive to innovation	The use of BDA may encourage innovation by providing valuable insights and new perspectives. This fosters a culture of experimentation where employees are motivated to explore new ideas and approaches without fear of error.	A81

organizational agility, enabling faster responses to cyber threats and improving the effectiveness of cybersecurity measures. This not only protects information assets but also promotes a culture of vigilance and proactive risk management [A160].

The introduction of BDA directly influences organizational models, requiring the development of new roles and capabilities. Many companies are investing in building analytical capabilities and infrastructure, creating specific positions for data scientists and analysts, and fostering cross-functional teams focused on data-driven projects [A36]. It also affects how organizations interact with external stakeholders, such as suppliers and data partners, influencing organizational policies and strategies to ensure access to data [A36]

In this context, the role of stakeholders—including customers, suppliers, and strategic partners—becomes essential, as these actors are increasingly involved in data-driven decision-making processes [A147]. This collaborative approach enables organizations to align their objectives with stakeholder expectations and market dynamics [A147].

Nevertheless, the integration of Big Data Analytics also brings complexities. While it can drive organizational performance, excessive dependence on data may lead to the erosion of competitive advantages, as expertise in data analysis can become generic and replicable across industries [A33]. To mitigate this risk, organizations are combining data-driven decision-making with managerial intuition, creating a balance that fosters more sustainable competitive advantage [A33].

Resistance among employees remains another barrier, particularly for those unfamiliar with or uncomfortable using BDA tools [A60]. This resistance is stronger when tools are perceived as complex or as threats to established work practices [A60]. To overcome this, it is fundamental to create an environment that encourages the use of BDA across the organization. This includes fostering a culture in which decision-makers favor data-driven methods and ensuring that the knowledge generated by BDA is embedded into organizational strategies and processes [A14]. It is also important that organizations develop managerial and technical skills to ensure the successful and sustainable implementation of BDA [A14].

Finally, companies must encourage employees to adopt new ideas and approaches based on insights obtained through data [A81]. This involves using insights to develop new products and services, identifying data needs to support decision-making, and reinforcing the belief in the value and role of data within the organization [A81].

The adoption of a data-driven culture is transforming organizations, replacing intuition-based decisions with choices informed by insights from large data sets. This promotes agility, transparency, and accountability, as well as fostering collaboration across departments. The use of Big Data Analytics (BDA) allows for greater management flexibility, faster responses to threats, and optimized processes, including supply chain sustainability. However, this transformation also requires companies to develop new technical skills and adapt their infrastructures to remain competitive and resilient in the market.

Despite its benefits, the integration of BDA presents challenges, such as resistance from employees unfamiliar with the tools and the possible erosion of competitive advantages as knowledge becomes more generic. To mitigate these risks, organizations are combining data-driven management with intuition. It is essential to create an environment that values data analysis, promotes a culture of continuous learning and innovation, and ensures that insights obtained through BDA directly influence business strategies and decisions.

5. Conclusions and Future Work

Organizations are increasingly adopting advanced methods and tools that guide decision-making in organizational process management, developing sophisticated strategies and building a data-driven culture. Digital technologies such as Big Data, Artificial Intelligence, and Decision Support Systems have a transformative impact, enabling better resource management and guiding business strategies. They allow the identification of patterns and valuable insights, generating benefits such as increased efficiency, cost reduction, and process innovation.

The adoption of Big Data Analytics (BDA) and its Analytical Capabilities (BDACs) brings significant advances to various organizational scenarios, particularly in improving business intelligence, risk management, competitive analysis, and supply chain optimization. Organizations that invest in process automation, data collection, processing, analysis, and visualization technologies achieve greater agility and efficiency in analyzing large volumes of data, overcoming challenges such as internal resistance and lack of infrastructure.

Even small and medium-sized enterprises (SMEs), by adopting a data-driven culture, can transform their operations, despite resource limitations. The main beneficiaries of this process include companies in dynamic sectors such as technology, finance, and supply chains, as well as institutions seeking competitiveness through innovation and sustainability. In these sectors, the use of BDA improves data management, optimizing internal operations and processes.

However, the implementation of BDA presents challenges related to the integration of large volumes of data, maintaining data quality, and addressing privacy and ethical issues. To overcome these barriers, organizations have invested in technological infrastructure, training, and robust data governance practices. The success of this transformation depends on the ability to align data strategies with organizational objectives and to foster a culture of continuous learning, where data analysis complements intuition and human judgment.

In addition to technical advances, the use of BDA provokes significant cultural changes within organizations. The transition to a data-driven culture is reshaping how employees make decisions and interact with information. This promotes greater flexibility and adaptability in operations, driving companies to become more agile and responsive to market changes.

Beyond synthesizing the existing body of knowledge, this study advances previous

works by integrating three dimensions that are often examined separately, technological methods and tools, organizational challenges, and cultural impacts related to Big Data Analytics (BDA) adoption. While prior studies typically focus on isolated perspectives, such as technical capabilities or specific organizational outcomes, our review provides a comprehensive and structured synthesis that connects these elements in the context of organizational process management. This integrated view not only clarifies how BDA effectively supports decision-making but also highlights the organizational conditions that facilitate or hinder its implementation. By mapping these relationships across 176 empirical and theoretical studies, the research offers a broader and more coherent understanding of the phenomenon, thus filling a gap in the fragmented literature and providing a foundation for more holistic future investigations.

Regarding suggestions for future research, the following directions are proposed:

- **Sectoral adaptation:** Future work could explore how different economic sectors are adapting these technologies to their specific needs and which sectors present greater resistance to the cultural change imposed by Big Data. This could be conducted through comparative analysis across sectors such as finance, healthcare, technology, industry, and retail, involving data collection through interviews with managers and technology experts, as well as case studies of companies that have already implemented these technologies.
- **Impact on employee well-being:** Since the increasing emphasis on data-driven decision-making may intensify performance pressure, future studies could analyze the effects of BDA on employee well-being. This research could adopt a mixed-methods approach, combining standardized questionnaires (such as stress and workplace well-being scales) with qualitative interviews to capture employees' perceptions of performance pressure associated with BDA. Case studies in companies that make intensive use of BDA could be conducted to observe and measure the direct effects on the organizational environment.

By combining qualitative and quantitative methodologies, these future studies can provide a comprehensive view of the impacts of emerging technologies on organizational dimensions and human well-being.

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