# A Systematic Review of the Benefits and Challenges of Data Analytics in Organizational Decision Making

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***Abstract*—Data analytics has been relied heavily in organizational decision-making, which allows accuracy, timeliness, and data-driven processes in a wide range of industries. These factors are influential as the figure and complexity of data are on the rise, along with problems like authentication, integration, and organizational resistance. The current study seeks to systematically review the benefits and challenges of data analytics on decision-making in different sectors using the PRISMA guidelines. A total of 32 articles published from 2020 until 2024 were identified through this review from reputable databases, including Scopus, Web of Science, IEEE Xplore, ProQuest, and Emerald Insight. These insights underscore the power of data analytics in driving change, enabling more accurate, faster, and aligned decision-making with organizational objectives. Challenges remain though, including the availability of broken data systems, hindrance due to a non-standardized norm across the whole sector, and resistance in places where data literacy is low or cultures resist data-driven practices. To mitigate the challenges, this review offers organizations practical recommendations for management. Companies that successfully incorporate analytics into their overall business strategies and create an organization-wide value for data and insights will be able to leverage analytics more effectively to enhance efficiency, encourage innovative growth, and navigate future disruptions. However, tackling these challenges is more than just optimizing performance—it is about future-proofing organizations in a world increasingly defined by data.**

***Keywords—Data analytics; decision-making; data-driven processes; big data analytics; systematic review***

## I. INTRODUCTION

Implementation of this method helps organizations in smart and accurate decision making which is an integral process of the global world today. This declaration comes atop a growing volume of data available today (and growing complexity as well), which presents both opportunity and challenges. Enabling this have been advances in technology such as machine learning and cloud computing that can analyze large amounts of data in real-time [1]. In particular, the use of data analytics in areas such as supply chain management, medical, and marketing is changing the way organizations can improve their actions and forecast future procedures in their working environment, based on [2], the analysis of large-scale data is the basis of customizing approaches, enabling organizations to adapt their services and products to the characteristics of each customer positively impacting the productivity and retention of customers. In addition, [3] noted that data analytics provides advantageous sustainable competitive advantages leading to innovation in emerging markets, thus directly enhancing strategic decision-making and all the different strategies that can be made. Moreover, [4] pointed out that big data analytics considerably enhance real-time decision-making, specifically in healthcare supply chains, by enabling efficient operations management and overcoming essential implementation hurdles.

In this sense, the identification of the main challenges in the field of data analytics for organizational decision-making highlights significant challenges related to data management and quality, as well as to the effective implementation of analytical methodologies. [5] Among these challenges, the integration of advanced techniques such as machine learning into traditional systems is especially problematic, due to the lack of clarity in objectives and limitations in organizational maturity for ad hoc projects. Instead [6], current approaches are focused on technology rather than socio-technical aspects, creating a disconnect between these technologies and their strategic and operational implementation. To cope with these challenges, methodologies focusing on end-to-end team, project, and data management have been introduced, a more holistic approach to data science projects. In organizational contexts [7], the successful integration of business analytics is contingent on a blend of organizational, technological, and environmental variables, which serve as driving forces behind its success.

This review provides strategic insights into leveraging data analytics to overcome barriers and optimize decision-making processes; by addressing these challenges with holistic approaches, organizations can better align technical tools with operational strategies, ultimately enhancing performance and driving meaningful innovation.

This study analyzes the effects of being data-driven on organizations, listing the benefits and challenges it presents as well as its strategic importance in varied industries. Furthermore, it offers actionable insights to assist organizations in effectively adopting analytics and deriving maximum value from it in their decision-making processes [8].

The rest of the paper is structured as follows: Section II discusses the related work. Section III explains the methods of carrying out this systematic review, including inclusion and exclusion criteria and sources of data. Results are described in Section IV, organized around major themes. An extended discussion of the implications, challenges, and opportunities arising from data analytics in organizations is covered in Section V. Finally, Section VI provides the conclusions and Section VII directions for future work.

## II. Related Work

Data analytics is increasingly critical for organizations, as it helps organizations make more informed decisions based on data. Prior research addressed the adoption of data analytics, benefits of data analytics, and challenges of data analytics per industry.

Multiple scholars have studied how big data analytics improves decision making and business intelligence. Patricio-Peralta et al. discussed the role of big data in shaping marketing approaches to enhance customer targeting and engagement using predictive analytics techniques [2]. Likewise, Al Nuaimi & Awofeso emphasized the vital significance of big data for healthcare supply chain management while also adding that it greatly supplements healthcare optimization leading to operational efficiency and be the followed standard [4]. Their studies are consistent with Rahman's systematic review on empowering business intelligence in healthcare capabilities, which show that data-driven decision-making improves resource allocation as well as patients' outcomes [9].

The quality and maturity of data is another important area of analytics adoption research. Galetsi et al. highlighted the challenge of data fragmentation and lack of interoperability as a key challenge that many organizations face to this day, limiting the reliability of insights derived from analytics [1]. Likewise, Al-Sai et al. presented a Big Data Maturity Model, emphasizing that the readiness of the organization for Big Data needs to be evaluated before integrating analytics into the decision-making process of the organization completely [5]. Hence, organizations focused on utilizing analytics must follow a stringent strategy for managing the data.

There have been several studies that also covered the obstacles to not adopting data analytics in organizations. Horani et al. highlights cultural and leadership challenges as major barriers, also mentioning that the lack of executive driving force can slow down analytics adoption [7]. Gonzales & Horita expanded on this by noting that bad visualization/analytics tools can mitigate against user engagement, thus potentially impacting efficacy in practical settings [10]. They also highlighted that a common factor across many sectors such as education and research, where streamlined data-driven strategies could benefit the decision-making process, is insufficient training in analytics tools [11].

Researchers also explored the contributions of advanced analytics and optimization techniques in decision making. Integrating these BI tools with strategic decision-making helps organizations make informed strategic choices with up-to-date insight [12]. Similarly, Akindote et al. demonstrated the use of geographic information systems (GIS) and analytics to improve decision-making in spatial planning and logistics [13]. Khanra et al. As an example toward the healthcare industry, demonstrating how analytics-oriented techniques can enhance patient care and reduce operational costs [14].

Similarly, implementation of big data analytics in various industries has also been extensively explored. Mansour & Bick delivered a systematic review of big data platforms employed in the healthcare digital transformation context and how artificial intelligence (AI)-based analytics have transformed diagnostics and treatment planning [15]. Tawil et al. analyzed the ways small and medium-sized enterprises (SMEs) in emerging economies utilize data analytics for a competitive edge, emphasizing opportunities and barriers in these contexts [16].

Therefore, while much academic research has contributed to the advances in data analytics, there are still areas that lack the necessary focus. Numerous studies indicate that although analytics adoption is growing, data standardization, integration, and culture acceptance still face challenges. The objective of this systematic review is to compile these insights and offer a complete evaluation of the advantages and disadvantages of data-driven decision-making in organizations.

## III. Methodology

PRISMA is selected for this study to conduct a systematic review. This offers a solid framework to analyze a large amount of data and evaluate their significance in organizations' decision-making processes [17]. The most up to date version, PRISMA 2020, brings important new changes which improve the transparency of systematic review and encourage reporting by all including with advances in methodology and terminology [9]. In certain domains, like strategic management, PRISMA is key to spotting gaps in the use of information within public organizations and small businesses, as it is a continuous improvement framework [18]. Additionally, this method has been useful in the industrial domain, to augment decision models and production systems with advanced technologies, such as AI and deep learning [19]. Moreover, PRISMA has been applied in research related to the digital transformation of bibliometric and systematic studies which have sought to resolve challenges associated with data recreation and meta-analysis [20].

### A. Identification

The identification phase focuses on the exhaustive search for articles relevant to the topic. Using recognized databases and specific keywords, potential publications are extracted for the review. According to Page et al. (2021), this phase establishes a systematic framework to ensure that relevant studies are included and that initial bias in source selection is minimized [17]. A systematic search for research data was performed in various known databases, including Scopus, Web of Science, IEEE Xplore, ProQuest, and Emerald Insight as illustrated in Fig. 1. The reason for selecting these databases is highly related to the data analytics applications in the organizational decision-making domain. To get sufficient coverage, certain keywords, along with Boolean operators, were utilized, e.g., "Data Analytics" OR "Big Data Analytics" AND "Decision Making" AND "Systematic Review", Although the study primarily focused on organizational and business contexts, some research from the healthcare field was included. This decision was made because their findings provided valuable insights that aligned with the broader goal of understanding how data analytics can enhance decision-making processes across various sectors. Furthermore, to ensure the currency of the findings, we applied a temporal range filter to select for only articles published in the last 5 years (2020-2024) as shown in Fig. 2. In total, 150 articles were identified after this first search.

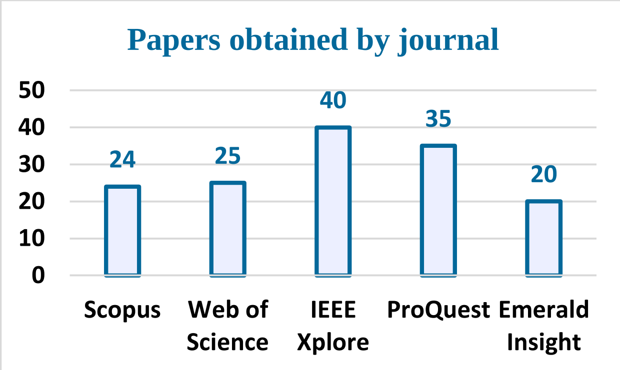


Fig. 1. Articles obtained by journal.

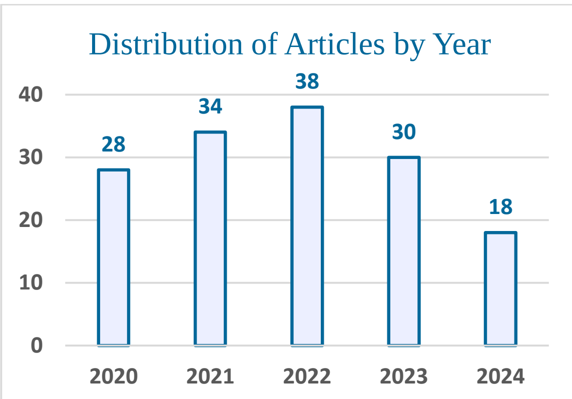


Fig. 2. Articles by publication year.

## B. Screening

In this phase, initial studies that are duplicates or irrelevant are removed by following pre-defined criteria. Shamseer et al. (2015) highlight that the current stage is important to reduce the effort of unnecessary data return and that only studies with a relevant focus proceed to the next stages [21]. Then we removed duplicate records, so this time we were left with 104 articles. In the next stage, the titles and abstracts of the rest of the articles were reviewed to determine relevance. Forty articles were rejected if they did not satisfy the established inclusion criteria, which included the following: their exclusive focus on domains such as health or education; failing to directly relate to organizational decision-making. Finally, 64 articles were reviewed in detail at this stage.

## C. Eligibility

So, the data from included studies were appraised in detail, to ascertain/assure the applicability of studies for systematic review. According to Galetsi et al. In this step, each publication was reviewed regarding its methodology and results to evaluate the quality of its content [22]. Further inclusion and exclusion criteria were applied during the full-text review of the 64 articles to assess study appropriateness. At this stage, 14 articles were excluded because they lacked sufficient methodological details, while another 18 were removed due to reasons such as not presenting results relevant to the organizational context or containing incomplete data. Ultimately, 32 articles met the eligibility criteria, forming a robust foundation for the analysis and ensuring the study's methodological rigor.

## D. Inclusion

Thus, in the systematic review inclusion phase, verifying the findings of relevant papers is crucial to ensure that the studies selected for inclusion within a review align with the review objectives. Anderson et al. (2021) stress the importance of this phase for the synthesis outcomes, where they must be aligned with the optimal criteria and appropriate synthesis techniques to generate trustworthy findings. Their findings highlight the significance of developing clear research questions and ensuring methodological transparency, so the studies included are both relevant and applicable. Such a rigorous approach provides for improved analysis, improving the likelihood that the findings are actionable, thereby making the contribution that much more useful for policy-makers and organizational leaders [23]. Following the methodology described in the previous section, we reviewed several articles, and 32 of them were appropriate for the systematic review. They provide a solid basis of how data analytics may help organizational decision-creating. These share topics varying from one to another including Big Data Maturity Model, drivers of business analytics adoption, and specific applications in various fields such as supply chain management; thus, showcasing the relevance of the same across various organizational frameworks.

## E. General Results

- Initial items identified: 150
- Duplicates removed: 46
- Articles discarded by title/abstract: 40
- Articles evaluated in full text: 64
- Articles excluded in full text: 32 (14 for lack of methodological data, 18 for other reasons)
- Final articles included: 32

Finally, we should clarify that of the total of 18 articles excluded for “other reasons”, the specific reasons are as follows: 10 articles were not relevant to the organizational context; 5 had insufficiently described methodologies; 3 were not available in their complete version; 3 were not available in their full version; and 3 were not available in their complete version.

Fig. 3 illustrates the application of the PRISMA Method, and the results obtained in each of its phases. This approach has allowed us to clearly and transparently structure and document the entire review process, from the initial identification of studies to the final selection of relevant articles. Using this paradigm not only guaranteed a more precise and complete interpretation but also enhanced the strength and fidelity of the study. We followed this systematic framework in order not only to source relevant studies but also to continuously reduce the risk of bias and to synthesize the evidence coherently so that the results are a true reflection of the current landscape of the topic investigated.

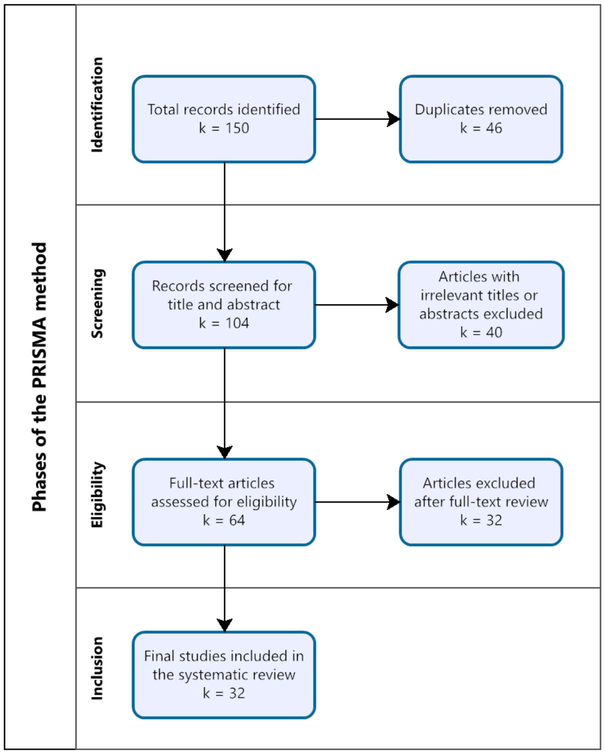


Fig. 3. PRISMA Method phases.

## IV. RESULTS

Findings were categorized and analyzed thematically into eight areas according to the final subset of included articles. Through the themes, we give an overview of the key issues and findings, capturing the range of contributions, with these summarized in Table I.

### A. *Data Quality and its Impact on Analytics*

The success of analytical initiatives hinges on the quality of data. Galetsi et al. demonstrated how data standards enable better interoperability and reduce fragmentation issues [1]. Al-Sai et al. emphasized the requirement to measure organizational maturity to implement big data effectively [5]. Lin et al. analyzed how the use of analytical systems can be integrated and usefully implemented when data is broken into parts [24]. Salazar-Reyna et al. Data Accessibility & Cleanliness: [25] highlighted the importance of accessible clean data as the most significant data-based barrier. Ifenthaler & Yau pointed out, "the stronger data literacy, the better analytic practices can be adopted" [26].

### B. *Organizational and Cultural Resilience*

Cultural and organizational resistance remains a major challenge. Horani et al. highlighted that lack of organizational leadership and support hinders the implementation of analytic tools [7]. Kew & Tasir noted that a lack of training in analytical tools limits their adoption in educational settings [11]. Gonzales & Horita highlighted that the lack of intuitive design in visual analytical tools generates rejection among end users [10]. Teniwut & Hasyim identified inefficient workflows as major barriers in supply chains [27].

TABLE I. ARTICLES GROUPED BY TOPIC

| Thematic | Related Articles | Brief Description of the Subject Matter |
|---|---|---|
| Data Quality and its Impact on Analytics | Galetsi et al. [1], Al-Sai et al. [5], Lin et al. [24], Salazar-Reyna et al. [25], Ifenthaler & Yau [26] | It focuses on how data quality affects the integration and effective use of analytical systems in various applications |
| Organizational and Cultural Resilience | Horani et al. [7], Kew & Tasir [11], Gonzales & Horita [10], Teniwut & Hasyim [27] | It examines the cultural and organizational barriers that hinder the implementation of analytical tools in different sectors. |
| Improved Decision Making | Komolafe et al. [3], Christenson Jr. & Goldstein [28], Aprijal et al. [29], Yang & Wang [30] | Analyzes how analytical tools support the identification of patterns and the optimization of strategic decisions. |
| Approaches to Optimization | Akindote et al. [13], Khanra et al. [14], Alnoukari [12], Soylu et al. [31] | Details the use of innovative approaches and advanced tools to improve operational efficiency and decision making. |
| Innovation in Specific Sectors | Tawil et al. [16], Ayuningtyas et al. [32], Raja et al. [34] | Explores how analytics is driving innovation in emerging industries and in the transformation of existing processes. |
| Use of Big Data in Decision Making | Rahman [9], Raja et al. [34], Matcha et al. [35], El Falah, Z., et al. [36] | Highlights the impact of big data in improving organizational decisions through personalization and advanced analytics. |
| Big Data Analytics Adoption Strategies | Patricio-Peralta et al. [2], Al Nuaimi & Awofeso [4], Astudillo et al. [6], Di Berardino & Vona [18] | Presents key strategies for effectively adopting big data in enterprise environments. |
| Critical Factors in the Adoption of Big Data Analytics | Dwilaga [19], Grander et al. [37], Hu, L., & Shu, Y. [38], Orlu et al. [39] | It examines the organizational and technological factors necessary for successful integration of analytics into complex systems. |

### C. *Improved Decision Making*

Analytical tools have transformed decision-making in different sectors. Komolafe et al. demonstrated that these tools generate competitive advantages by identifying patterns in emerging markets [3]. Christenson Jr. & Goldstein highlighted the positive impact of analytics on risk mitigation and optimization of strategic processes [28]. Aprijal et al. found that analytics in manufacturing and retail reduce operating costs and improve efficiency [29]. Yang & Wang analyzed how systematic evaluations optimize scalability in big data environments [30].

### D. *Approaches to Optimization*

Innovative tools and approaches have overcome specific problems. Akindote et al. explored the integration of GIS and analytical tools to optimize decision-making systems [13]. Khanra et al. observed that analytical tools significantly improve operational efficiency in healthcare systems [14]. Alnoukari highlighted how business intelligence tools help organizations optimize strategic decisions through advanced data analysis [12]. Soylu et al. showed how these tools increase transparency in public administration [31].

### E. Innovation in Specific Sectors

Analytics has generated significant innovations in multiple sectors. Mansour & Bick explored how big data has scaled digital transformation in the healthcare sector [15]. Tawil et al. highlighted barriers and opportunities for data-driven decision-making in emerging economies, fostering innovation in various sectors [16]. Ayuningtyas et al. highlighted applications of analytics in emerging sectors to optimize organizational processes [32]. Rakesh et al. proposed approaches to improve scalability in big data, facilitating the use of these technologies in varied sectors [33].

### F. Use of Big Data in Decision Making

Big data has been shown to improve the quality of organizational decisions. Rahman proposed integration frameworks to maximize the impact of business intelligence [9]. Raja et al. identified how big data increases operational efficiency in healthcare systems [34]. Matcha et al. found that learning analytics dashboards facilitate decision-making in educational settings by providing more personalized information [35]. El Falah, Z., et al. showed how intelligent approaches to data analytics can transform the ability of organizations to process and apply big data in their strategic decisions [36].

### G. Big Data Analytics Adoption Strategies

Regarding strategies for big data adoption, Patricio-Peralta et al. emphasized the need for trained personnel to maximize the marketing impact [2]. Al Nuaimi & Awofeso pointed out that infrastructure is key to optimizing supply chains [4]. Astudillo et al. proposed user-centric methodologies to integrate analytics in organizations [6]. Di Berardino & Vona identified analytical frameworks that facilitate strategic decision-making in corporate environments [18].

### H. Critical Factors in the Adoption of Big Data Analytics

Key factors include organizational maturity and cultural support. Dwilaga proposed optimized decision models to overcome problems in complex industrial processes [19]. Grander et al. highlighted how advanced analytical tools can generate significant value in decision support systems [37]. Hu, L., & Shu, Y. developed intelligent approaches to analyze complex data, improving the effectiveness of strategic decisions [38]. Orlu et al. explored strategies to improve decision-making under uncertainty [39].

The findings of this study provide valuable insights for organizations seeking to navigate the complexities of data-driven decision-making. Only with the knowledge of the main barriers, like fragmented data systems and cultural resistance, can leaders work their way around these and craft strategies that would ensure that they foster a data-driven culture and still allocate funds towards building robust data infrastructures. These actions would not only surmount the active challenges but would also enable organizations to reap the full benefits of analytics: faster, more nuanced and integrative decision-making aligned with strategic objectives. With these strategies, organizations can promote innovation and maintain their competitive edge, enabling them to achieve real growth in the data-driven world.

## V. Discussion

It dives into the insights that were identified and arranged into 8 Paramount Sections -- The Relation of Data Quality to Analytics, Organizational and Culture Resistance Towards Analytics Adoption, Tools and Techniques in Optimizing Analytics, The Providing of Strategies for Big Data Adoption, Industry-Driven Innovations, How Big Data Impacts Decision Making, Major Elements of Factors in Big Data Analytics Adoption and Influence, New Horizons of Decision Making. The point is, these categories afford a total framework for data-driven decision-making impact between industries. The discussion also reviews barriers to analytics adoption by organizations, while focusing on the advances made possible through more advanced tools and techniques. As a whole, shaping the advantages and realities in tens of thousands of organizations, these findings provide a comprehensive perspective on how to use data analytics, advancing towards whether organizations tune the best practices of data analytics or hinder the process of data analytics to sustain innovative outcomes in these highly data dependent enterprises.

### A. Data Quality and its Impact on Analytics

The results reaffirm that data quality is a critical foundation for analytical initiatives to succeed. Galetsi et al. [1] and Lin et al. [24] highlight that fragmented data systems and a lack of interoperability are significant impediments to organizations' ability to seamlessly integrate data into their analytics systems. Al-Sai et al. big data requires an organization to be matured [5], as well, and Ifenthaler and Yau [26] argue that a crucial first step toward adopting analytics practices is increasing data literacy. But, notwithstanding those attempts, issues, such as setting adequate data quality thresholds or data access, remain Salazar-Reyna et al. [25] continue to get in the way of setting up effective analytics systems. These issues cannot be overcome in isolation: solving them requires a system-wide response that brings together technological and organizational solutions to maximize the potential of analytics.

### B. Organizational and Cultural Resilience

Resistance at both the cultural and organizational levels continue to pose a major challenge to adopting analytics across various industries. Horani et al. [7] identified the lack of strong leadership and organizational support as critical barriers that hinder successful analytics adoption. Similarly, Kew and Tasir [26] found that inadequate training remains a significant obstacle, particularly in educational institutions where analytics has the potential to transform decision-making processes. To overcome these barriers, fostering a culture that values data-driven decision-making, supported by consistent leadership and tailored training programs, is essential for ensuring the effective implementation of analytics. These findings underscore the need for targeted strategies to address both leadership and skill development to facilitate the broader integration of analytics practices. Gonzales & Horita [10] stated how non-intuitive designs of analytical tools discourage the use of those tools and Teniwut & Hasyim [27] reported that disorganized workflows amplify the resistance to change in supply chains. These findings underscore the need for better training, stronger leadership, and redesigned technologies that make adoption easier.

## C. Improved Decision Making

The transformation of decision-making through data analytics Komolafe et al. [3] showed analytics support competitive advantage based on patterns in born-global markets. According to Christenson Jr. & Goldstein [28], its impact is to provide better risk mitigation and optimize the strategic process. In addition, furthermore, demonstration of these techniques in industrial contexts has been made by Aprijal et al. [29] and Yang & Wang [30] describing relevant operational cost and scalation benefits for the solution. However, certain segments are struggling to implement these solutions, indicating the requirement for more bespoke solutions.

## D. Approaches to Optimization

Such innovative tools and strategic approaches have been critical for the optimization of analytical systems. Akindote et al [13], Soylu et al. [31] also looked into how GIS and big data can be integrated to enhance transparency and decision-making in public administration. Business Intelligence tools play an important role in strategic decision solidifying, Alnoukari [12]. Khanra et al [14], on the other hand, demonstrated that these tools can increase efficiency in healthcare systems. However, problems related to interoperability and standardization limit effective implementation.

## E. Innovation in Specific Sectors

Data analytics has generated disruptive innovations in specific sectors. Mansour & Bick [15] evidenced how big data is driving digital transformation in healthcare, while Tawil et al. [16] highlighted its impact in emerging economies. Ayuningtyas et al [32] and Rakesh et al. [33] discussed how these technologies optimize organizational processes and promote scalability. While these advances are promising, infrastructure and cultural barriers continue to limit their widespread adoption.

## F. Use of Big Data in Decision Making

Big data has significantly improved the quality of organizational decisions. Rahman [9] developed frameworks that maximize the impact of business intelligence, while Raja et al. [34] evidenced operational improvements in healthcare systems. Matcha et al. [35] highlighted the benefits of analytic dashboards in educational settings. Finally, El Falah et al. [36] demonstrated how intelligent approaches in data analytics strengthen the strategic capability of organizations. However, the lack of alignment between strategic objectives and analytical capabilities persists as a challenge.

## G. Big Data Analytics Adoption Strategies

Patricio-Peralta et al [2] stressed the importance of having trained personnel to maximize the impact of big data in marketing. Al Nuaimi & Awofeso [4] identified infrastructure as a critical factor in supply chains, while Astudillo et al. [6] and Di Berardino & Vona [18] proposed user-centric approaches and analytical frameworks that foster strategic decision-making. Although these strategies are fundamental, resistance to change and lack of specialized resources limit their effectiveness.

## H. Critical Factors in the Adoption of Big Data Analytics

Key factors include organizational maturity, cultural support, and strategic focus. Dwilaga [19] proposed optimized models for industrial processes, while Grander et al. [37] highlighted the value generated by advanced tools. Hu, L., & Shu, Y. [38] evidenced that intelligent approaches improve the effectiveness of strategic decisions, and Orlu et al. [39] explored strategies to mitigate uncertainties in big data contexts. However, challenges persist in widespread implementation due to the lack of integration between departments.

## I. Geographical Distribution of Scientific Contributions

Fig. 4 provides an overview of the distribution of articles by continent, highlighting the scientific contributions to the field of data analytics and decision-making. This analysis is key to understanding regional dynamics and priorities in research. The Americas leads with 15 articles, with the United States standing out as the largest contributor with 9 publications, reaffirming its prominent position in this field. Europe, contributing 12 articles, demonstrates a strong and diverse presence in the field, with significant contributions from countries like the United Kingdom and Germany. Asia, with 8 articles, showcases remarkable growth, driven by emerging economies such as India and China, solidifying its expanding role in this domain. Oceania, with 3 articles, maintains a steady but smaller contribution, while Africa, represented by only 1 article, highlights a clear gap and an opportunity to encourage research and development in the region. This distribution not only reveals regional disparities but also underscores the importance of fostering global collaborations to bridge these gaps and accelerate progress in underrepresented areas.

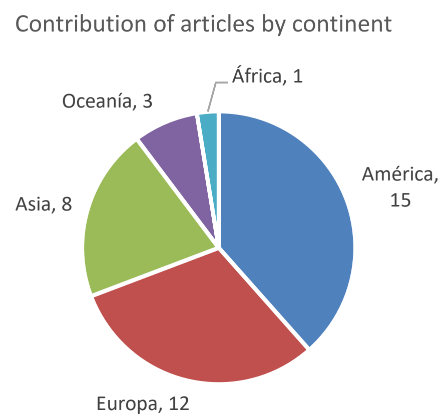


Fig. 4. Contribution of articles.

## J. Methodological Diversity in Data Analytics and Decision Making

One main point of interest is the disparity between the number of techniques (65) compared to the number of articles analyzed (39) as detailed in Table II, which looks at the techniques and methodologies used in the reviewed articles. This difference is a testament to the effective diversity of methodology run in data analytics and decision-making. One of the main reasons this happens is the routine use of combining complementary methods in a single study. This method allows researchers to tackle issues from different angles and, as a result, create more resilient and all-encompassing solutions. Such a study could combine predictive analytics and machine learning algorithms to identify trends and predict future outcomes, while at the same time applying data visualization tools to expose the insight in a more digestible and telling manner.

TABLE II. TECHNIQUE / METHODOLOGY

| Technique / Methodology | Quantity |
|---|---|
| Systematic Review | 15 |
| Big Data Analysis | 10 |
| Decision Modeling | 8 |
| Data Mining | 7 |
| Predictive Analytics | 6 |
| Machine Learning | 5 |
| Analytics Dashboards | 4 |
| Narrative Analysis | 3 |
| Decision Support Systems | 3 |
| Maturity Assessment | 2 |
| Assessment Framework | 2 |

Additionally, this diversity in methodology is a reflection of the inherently interdisciplinary nature of the field, with methodologies borrowed from domains such as statistics, artificial intelligence, and organizational management [8]. Most of the studies use some secondary/supplementary methods to augment or triangulate the analysis obtained using the primary method. This is especially prevalent in studies that seek to compare the relative effectiveness of different implementations or to investigate different applications in the same setting. Another reason for this use of multiple approaches is the need to customize solutions according to the industry, for example, healthcare, manufacturing, or logistics which usually face complex and interdependent challenges that require more of a holistic approach.

### *K. Study Limitations*

To be transparent about what was found and the scope of that finding, the table below sets out the main limitations identified. However, recognizing these limitations is key to appropriately assessing the results and directing future research efforts.

To aid the interpretation of the results and support transparency about the boundaries of the study, Table III below summarizes the key limitations we identified. It is necessary to consider these limitations in correctly interpreting the results and guiding the future at the same time.

The benefits and challenges uncovered in this study serve as a roadmap for organizations striving to embrace data analytics effectively. Acknowledging benefits like faster decision-making, enhanced accuracy and better alignment with strategic objectives enables leaders to advocate for analytics investments. Additionally, by learning about common pain points such as fragmented data systems and cultural resistance, organizations can better prepare for roadblocks and work proactively to counter them. A comprehensive approach that harmonizes technology with strategic functions can cultivate an ecosystem where data-driven insights thrive. This not only helps in the effective adoption of analytics but also promotes the innovative spirit and maintains the competitiveness of organizations in today's world of data.

TABLE III. STUDY LIMITATIONS

| Limitation | Description |
|---|---|
| Restricted Temporal Coverage | The review focuses on articles published between 2020 and 2024, which may exclude earlier studies that could offer additional perspectives or alternative approaches to data analytics adoption and impact. |
| Database Selection and Publication Bias | The review uses well-known databases (Scopus, Web of Science, IEEE Xplore, ProQuest, and Emerald Insight). This might lead to the exclusion of relevant studies from grey literature or other unindexed sources, potentially affecting the representativeness of the findings. |
| Reliance on the Quality of Included Studies | The robustness of the conclusions depends on the methodological rigor of the 32 articles reviewed. Any limitations in the methodology of the included studies could influence the reliability and validity of the overall synthesis. |
| Lack of Empirical Validation | The study is based primarily on a systematic literature review without supplementary empirical or experimental validation to confirm the effectiveness of the proposed recommendations or conclusions in real-world settings. |
| Limited Applicability to Certain Sectors | Although the review includes studies from various sectors (e.g., healthcare, marketing, logistics, manufacturing, education, e-commerce), many examples are concentrated in healthcare, marketing, and supply chain management. This may limit the generalizability of the findings to sectors with different challenges. |

## VI. CONCLUSION

The systematic review shows that data analytics significantly contributes to changing the way decisions are being made in organizations. Synthesizing a body of 32 studies published between the years of 2020–2024, the review distilled eight key themes—including data quality and organizational resilience, to approaches for optimization and strategies for adoption—that together depict the facilitators and impediments to adopting data-driven decision-making.

The key findings highlight the enhanced accuracy, timeliness, and competitive advantage through data analytics, albeit under considerable challenges. These aspects are said to be the likes of data fragmentation, insufficient interoperability, organizational resistance as well as the lack of holistic plans integrating both the technical and socio-cultural factors.

An important value added of this review is its full template of themes revealing the factors enabling or constraining successful integration of analytics. The synthesis highlights the need to improve data quality, create accountability for data management and use, and establish strong and holistic approaches to addressing barriers identified to support data driven development.

For practical validation, future studies should compare and contrast the effectiveness of varying data analytics methodologies. This work will further shape and guide the current understanding of how and when to implement analytics solutions in various organizational contexts through concrete recommendations.

To conclude, data analytics have proven to be essential for enhancing organizational efficiency and making strategic data-driven decisions. However, to achieve these advantages, it is important to address the challenges identified through specific empirical investigation and focus on integrative, adaptive strategies.

## VII. FUTURE WORK

This study has illuminated both the significant progress and persistent challenges in leveraging data analytics to enhance organizational decision-making. Building on these findings, future research should focus on key areas that can drive meaningful advancements and ensure sustainable growth in this field.

One of the essential factors is the uniformity of the quality of data, according to which the quality of data will be ensured, particularly for organizations that are working through different industries and geographies. It is also essential to understand the socio-cultural dynamics that shape how these analytics tools are adopted, as this is often the determining factor of where such initiatives succeed or fail. One way to leverage its transformative potential in sectors that have not applied data analytics (for example education, environment, management).

Another exciting opportunity is building intuitive, frictionless tools made for the needs of developing economies. These tools can democratize access to advanced analytics and bridge technological gaps. Real-time processing of the data collected by IoT devices through incorporation into analytical processes can lead to new innovative opportunities for improving the efficiency of decision-making processes in organizations. How might we develop strong socio-technical frameworks to help with this problem, another area where more research is needed, as theory has yet to grapple with the cultural complexity that can result through this process, which puts together technology, organizational processes, and human factors in an interdisciplinary context?

While this systematic review aims to synthesize the literature available, it is worth noting that most of the studies being reviewed offer solutions without strong empirical validations of these or direct comparisons with other approaches. Although our work was not an independent experimental validation—in line with the systematic review format—we recognize the need for empirical validation in establishing the real-world utility of data analytics approaches. Future work might include a meta-analysis of validation results from the primary studies, or even empirical comparative studies of well-justified approaches under comparable conditions. Such initiatives would deepen our insights about the relative advantages and disadvantages of each approach and provide more refined guidelines of best practices about how to employ data analytics in organizational decision making.

There is also continued important research on how to optimize analytical processes. Hybrid methods have been found useful in multiple domains, such as using GIS with analytics for supply chain optimization [13], implementing advanced tools for operational improvements in healthcare [14], and using a decision support system that can reduce cost and performance-focused management in logistics environments [27]. When developing targeted, sector-specific solutions that build upon the current tools available as well as novel approaches, these insights should serve as a guide.

Finally, the eight themes identified in this study provide a roadmap for advancing knowledge and application in data analytics. Each theme, ranging from data quality to big data adoption strategies, offers distinct opportunities for exploration, ensuring that future research addresses challenges holistically while maximizing the benefits of analytics in decision-making. By focusing on these areas, researchers can ensure that analytics evolves as an inclusive, adaptable, and transformative force across diverse organizational and societal contexts. These proposals are presented in detail in Table IV, allowing a clear and organized visualization of the research priorities in each thematic area.

TABLE IV. FUTURE RESEARCH DIRECTIONS BY THEMATIC AREA

| Thematical | Details |
|---|---|
| Data Quality and its Impact on Analytics | Explore automated tools to ensure real-time data quality. Investigate global standards to improve system interoperability. Evaluate case studies of fragmented data in complex organizations. |
| Organizational and Cultural Resilience | Design training programs to reduce resistance to the use of analytical tools. Study the socio-cultural factors that influence the adoption of analytics in different regions. |
| Improved Decision Making | Develop hybrid models that combine machine learning with traditional decision-making approaches. Evaluate the impact of analytics on long-term strategic decisions in key industries. |
| Approaches to Optimization | Test the integration of emerging technologies, such as blockchain, into analytics systems. Design frameworks for the simultaneous implementation of analytics and GIS in industrial contexts. |
| Innovation in Specific Sectors | Analyze case studies in emerging sectors such as agriculture and renewable energy. Evaluate the feasibility of advanced analytics in low resource sectors. |
| Use of Big Data in Decision Making | Study the effectiveness of public policies to foster the adoption of big data in emerging economies. Propose strategies to reduce implementation costs in small and medium enterprises. |
| Big Data Analytics Adoption Strategies | Investigate how big data can improve prediction and planning in global crises. Develop specific tools for the integration of big data in governmental decision-making processes. |
| Critical Factors in the Adoption of Big Data Analytics | Identify and measure new key indicators of success in big data adoption. Explore how cultural differences influence adoption rates in different organizational contexts. |

## REFERENCES

[1] Galetsi, P., Katsaliaki, K., & Kumar, S. (2019). Values, challenges and future directions of big data analytics in healthcare: A systematic review. Social Science & Medicine. https://doi.org/10.1016/j.socscimed.2019.112533

[2] Patricio-Peralta, C., Mondragon, J. Z., Terrones, L. S., & Ramirez Villacorta, J. (2024). Big data analysis and its impact on the marketing industry: a systematic review. Indonesian Journal of Electrical Engineering and Computer Science. https://doi.org/10.11591/ijeecs.v35.i2.pp1032-1040

[3] Komolafe, A. M., Aderotoye, I. A., Abiona, O. O., Adewusi, A. O., Obijuru, A., Modupe, O. T., & Oyeniran, O. C. (2024). Harnessing business analytics for gaining competitive advantage in emerging

markets: A systematic review of approaches and outcomes. International Journal of Management & Entrepreneurship Research. https://doi.org/10.51594/ijmer.v6i3.939

[4] Al Nuaimi, D., & Awofeso, N. (2024). The Value of Applying Big Data Analytics in Health Supply Chain Management. F1000Research. https://doi.org/10.12688/f1000research.156525.1

[5] Al-Sai, Z., Husin, M., Syed-Mohamad, S. M., Abdullah, R., Zitar, R. A., Abualigah, L., & Gandomi, A. (2022). Big Data Maturity Assessment Models: A Systematic Literature Review. Big Data and Cognitive Computing. https://doi.org/10.3390/bdcc7010002

[6] Astudillo, B. K., Santórum, M., & Aguilar, J. (2020). A Methodology for Data Analytics Based on Organizational Characterization Through a User-Centered Design. Journal of Organizational Analytics. https://doi.org/10.1007/978-3-030-51828-8_20

[7] Horani, O., Khatibi, A., Al-Soud, A., Tham, J., & Al-Adwan, A. (2023). Determining the Factors Influencing Business Analytics Adoption at Organizational Level: A Systematic Literature Review. Big Data and Cognitive Computing. https://doi.org/10.3390/bdcc7030125

[8] Szukits, Á., Móricz, P. Towards data-driven decision making: the role of analytical culture and centralization efforts. Rev Manag Sci 18, 2849–2887 (2024). https://doi.org/10.1007/s11846-023-00694-1

[9] Rahman, M. M. (2024). Systematic Review of Business Intelligence and Analytics Capabilities in Healthcare Using PRISMA. International Journal of Health and Medical. https://doi.org/10.62304/ijhm.v1i04.207

[10] Gustavo Romão Gonzales and Flávio Horita. 2020. Supporting visual analytics in decision support system: a systematic mapping study. In Proceedings of the 19th Brazilian Symposium on Human Factors in Computing Systems (IHC '20). Association for Computing Machinery, New York, NY, USA, Article 34, 1–10. https://doi.org/10.1145/3424953.3426483

[11] Kew, S.N., & Tasir, Z. (2022). Learning Analytics in Online Learning Environment: A Systematic Review on the Focuses and the Types of Student-Related Analytics Data. Tech Know Learn 27, 405–427. https://doi.org/10.1007/s10758-021-09541-2

[12] Alnoukari, M. (2020). Examining the Organizational Impact of Business Intelligence and Big Data Based on Management Theory. Business Analytics Journal. https://doi.org/10.37380/jisib.v10i3.637

[13] Akindote, O. J., et al. (2023). Comparative Review of Big Data Analytics and GIS. International Journal of Geographic Information Systems. https://doi.org/10.30574/wjarr.2023.20.3.2589

[14] Khanra, S., et al. (2020). Big Data Analytics in Healthcare: A Systematic Literature Review. Journal of Healthcare Informatics. https://doi.org/10.1080/17517575.2020.1812005

[15] Mansour T., Bick M. A Systematic Literature Review of Big Data Analytics in Healthcare Digital Transformation. JDS, 6(1), 3–17, (2024). https://doi.org/10.33847/2686-8296.6.1_1

[16] Tawil, A. -R. H., Mohamed, M., Schmoor, X., Vlachos, K., & Haidar, D. (2024). Trends and Challenges towards Effective Data-Driven Decision Making in UK Small and Medium-Sized Enterprises: Case Studies and Lessons Learnt from the Analysis of 85 Small and Medium-Sized Enterprises. Big Data and Cognitive Computing, 8(7), 79. https://doi.org/10.3390/bdcc8070079

[17] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. The BMJ. https://doi.org/10.1136/bmj.n71

[18] Di Berardino, D., & Vona, S. (2023). Discovering the Relationship Between Big Data and Decision Making. European Scientific Journal, ESJ. https://doi.org/10.19044/esj.2023.v19n19p1

[19] Dwilaga, A. T. (2023). Decision Model and Industry Optimization in Production: A Systematic Literature Review. Sainteks: Jurnal Sains dan Teknik. https://doi.org/10.37577/sainteks.v5i1.528

[20] Almasri, H., Zakuan, N., Amer, M., & Majid, M. R. (2021). A developed systematic literature review procedure with application in the field of digital transformation. Studies of Applied Economics. https://doi.org/10.25115/eea.v39i4.4559

[21] Rethlefsen, M.L., Kirtley, S., Waffenschmidt, S. et al. PRISMA-S: an extension to the PRISMA Statement for Reporting Literature Searches in Systematic Reviews. Syst Rev 10, 39 (2021). https://doi.org/10.1186/s13643-020-01542-z

[22] Kahale, L. A., Hamadeh, G. N., & Ghalayini, W. (2021). Assessing the methodological quality of systematic reviews: insights from the AMSTAR-2 tool. F1000Research. https://doi.org/10.12688/f1000research.28686.1

[23] Anderson, R., Booth, A., Eastwood, A., Rodgers, M., Shaw, L., Thompson Coon, J., Briscoe, S., Cantrell, A., Chambers, D., Goyder, E., Nunns, M., Preston, L., Raine, G., & Thomas, S. (2021). Synthesis for health services and policy: case studies in the scoping of reviews. Health Services and Delivery Research, 9(15). https://doi.org/10.3310/hsdr09150

[24] Lin, J.S., Murad, M.H., Leas, B. et al. A Narrative Review and Proposed Framework for Using Health System Data with Systematic Reviews to Support Decision-making. J GEN INTERN MED 35, 1830–1835 (2020). https://doi.org/10.1007/s11606-020-05783-5

[25] Salazar-Reyna, R., Gonzalez-Aleu, F., Granda-Gutierrez, E.M.A., Diaz-Ramirez, J., Garza-Reyes, J.A. and Kumar, A. (2022), "A systematic literature review of data science, data analytics and machine learning applied to healthcare engineering systems", Management Decision, Vol. 60 No. 2, pp. 300-319. https://doi.org/10.1108/MD-01-2020-0035

[26] Ifenthaler, D., & Yau, J. Y. K. (2021). Supporting Teaching Staff Through Data Analytics. Technology, Knowledge and Learning. https://doi.org/10.14742/ascilite2021.0105

[27] Teniwut, W.A., & Hasyim, C.L. (2020). Decision support system in supply chain: A systematic literature review. Uncertain Supply Chain Management, 8, 131-148. https://doi.org/10.5267/j.uscm.2019.7.009

[28] Christenson Jr., A.P., & Goldstein, W.S. (2022). Impact of data analytics in transforming the decision-making process. Business & IT. https://doi.org/10.14311/bit.2022.01.09

[29] Aprijal, R., Siregar, I., Siahaan, A., & Marlina, L. (2024). Utilization of Data Analytics to Enhance Operational Efficiency in Manufacturing Companies. Journal of Computer Networks, Architecture and High Performance Computing. https://doi.org/10.47709/cnahpc.v6i2.3723

[30] Yang, F., Wang, M. A review of systematic evaluation and improvement in the big data environment. Front. Eng. Manag. 7, 27–46 (2020). https://doi.org/10.1007/s42524-020-0092-6

[31] Soylu, A., Corcho, Ó., Elvesæter, B., Badenes-Olmedo, C., Yedro-Martínez, F., Kovacic, M., Posinkovic, M., Medvešček, M., Makgill, I., Taggart, C., Simperl, E., Lech, T., & Roman, D. (2022). Data Quality Barriers for Transparency in Public Procurement. Inf., 13, 99. https://doi.org/10.3390/info13020099

[32] Ayuningtyas, A., et al. (2023). Big Data Analysis and Its Utilization for Business Decision-Making. World Journal of Business Analytics. https://doi.org/10.58812/wsist.v1i01.177

[33] Raut, R., Narwane, V., Mangla, S., Yadav, V., Narkhede, B., & Luthra, S. (2021). Unlocking causal relations of barriers to big data analytics in manufacturing firms. Ind. Manag. Data Syst., 121, 1939-1968. https://doi.org/10.1108/IMDS-02-2020-0066

[34] Raja, Rakesh, Mukherjee, Indrajit, Sarkar, Bikash Kanti, A Systematic Review of Healthcare Big Data, Scientific Programming, 2020, 5471849, 15 pages, 2020. https://doi.org/10.1155/2020/5471849

[35] Matcha, W., et al. (2020). Learning Analytics Dashboards: A Systematic Review. Educational Data Analytics Journal. https://doi.org/10.1109/TLT.2019.2916802

[36] EL FALAH Zineb, RAFALIA Najat and ABOUCHABAKA Jaafar, "An Intelligent Approach for Data Analysis and Decision Making in Big Data: A Case Study on E-commerce Industry" International Journal of Advanced Computer Science and Applications(IJACSA), 12(7), 2021. http://dx.doi.org/10.14569/IJACSA.2021.0120783

[37] Grander, Gustavo & Silva, Luciano & Santibanez Gonzalez, Ernesto. (2021). Big data as a value generator in decision support systems: a literature review. Revista de Gestão. ahead-of-print. https://doi.org/10.1108/REGE-03-2020-0014

[38] Lei Hu and Yangxia Shu, "Enhancing Decision-Making with Data Science in the Internet of Things Environments" International Journal of Advanced Computer Science and Applications(IJACSA), 14(9), 2023. http://dx.doi.org/10.14569/IJACSA.2023.01409120

[39] Orlu, G. U., Abdullah, R. B., Zaremohzzabieh, Z., Jusoh, Y. Y., Asadi, S., Qasem, Y. A. M., Nor, R. N. H., & Mohd Nasir, W. M. H. b. (2023). A Systematic Review of Literature on Sustaining Decision-Making in Healthcare Organizations Amid Imperfect Information in the Big Data Era. Sustainability, 15(21), 15476. https://doi.org/10.3390/su152115476