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Empowering Decision-Making through Big Data Analytics: A Narrative Review of Techniques, Tools, and Industrial Applications

Aryo Nugroho
Universitas PGRI Adibuana Surabaya, Indonesia
Correspondent: nugroho@unipasby.ac.id

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ABSTRACT: Big Data Analytics (BDA) has become a pivotal enabler of data-driven decision-making across various industrial sectors. This narrative review aims to synthesize existing literature on BDA techniques, tools, and applications to identify their role and impact in decision support systems. The review draws upon scholarly databases such as Scopus, IEEE Xplore, and Google Scholar, utilizing a systematic search strategy with Boolean keyword combinations to retrieve relevant literature. Studies were screened based on inclusion and exclusion criteria, focusing on empirical findings and practical applications of BDA across domains. Findings reveal that techniques such as data mining, predictive analytics, and machine learning offer enhanced accuracy and real-time capabilities, leading to better outcomes in healthcare diagnostics, manufacturing efficiency, and logistics optimization. The utilization of platforms like Hadoop, Spark, and Tableau demonstrates both functional versatility and implementation challenges, influenced by cost, infrastructure, and human capital readiness. Furthermore, the success of BDA initiatives is closely linked to organizational factors including data quality and workforce expertise. Systemic barriers such as strict data policies, fragmented IT infrastructures, and limited data access in low-resource settings impede optimal BDA deployment. This review underscores the need for strategic policy reforms, technological investments, and capacity building to realize the full potential of BDA. By addressing existing limitations and supporting future research directions, organizations can harness BDA to enable informed, agile, and sustainable decision-making.

Keywords: Big Data Analytics, Decision Support Systems, Machine Learning, Predictive Analytics, Industry Applications, Data-Driven Decision-Making, Organizational Factors.

INTRODUCTION

In recent years, the exponential growth of data has underscored the importance of Big Data Analytics (BDA) as a framework for processing large volumes of structured and unstructured data. Unlike generic data analysis, BDA specifically enhances decision-making by enabling organizations across sectors—such as healthcare, logistics, and manufacturing—to extract actionable insights and gain measurable strategic advantages. This growing relevance has been further accentuated by the integration of advanced technologies such as Artificial Intelligence (AI) and Machine Learning (ML), which have enhanced BDA's capabilities in processing, interpreting, and predicting outcomes from complex data streams (Redondo et al., 2020). As such, BDA is not only a technical innovation but also a transformative instrument for organizational strategy and operational efficiency.

In light of this, a considerable body of research has been devoted to exploring BDA's applications and implications. For instance, Kumar and Singh (2019) and Naik et al. (2022) highlighted how BDA has significantly advanced the healthcare sector by enabling predictive diagnostics and population health management. Similarly, Pawar and Dhumal (2024) underscored the transformative role of technology in leadership and strategic management, facilitated through real-time insights derived from BDA. Furthermore, the industrial sector has seen a shift toward smarter, leaner manufacturing systems using BDA-driven intelligence (Tripathi et al., 2024). In logistics and supply chain management, the utility of BDA for forecasting, inventory optimization, and route planning is increasingly well-documented (Udegbe et al., 2019). Despite the varied contexts, the unifying thread in the literature is the recognition of BDA as a catalyst for data-informed decision-making.

Empirical studies further support the relevance of BDA. Organizations integrating BDA into decision-making report reduced operational costs, improved service delivery, and heightened customer satisfaction. These outcomes illustrate the tangible advantages of data-driven approaches.

Another crucial aspect of BDA's contribution is its capacity for real-time analysis. The combination of high-speed data processing with visualization techniques has empowered organizations to respond swiftly to dynamic environments. As noted by Protopsaltis et al. (2020), visual analytics tools enhance the interpretability of data, thereby accelerating strategic responses. This is particularly relevant in industries where decision windows are narrow and the costs of delayed or inaccurate decisions are high. In these contexts, BDA not only supports but redefines the decision-making process, shifting it from reactive to proactive.

Nevertheless, despite its promising potential, BDA implementation is fraught with challenges. One of the most pervasive issues is data quality and integrity. Inaccurate, incomplete, or inconsistent data can significantly impair the validity of analytical outcomes, leading to suboptimal decisions (Naik et al., 2022; Kumar & Singh, 2019). Many organizations struggle with ensuring that their data repositories are clean, integrated, and representative of real-world conditions. This problem is exacerbated in contexts where data governance practices are weak or underdeveloped.

Another key challenge lies in the availability of skilled personnel. Effective use of BDA requires a workforce proficient in data science, machine learning, and domain-specific knowledge. However, the literature consistently points to a shortage of such expertise in many organizations (Pawar & Dhumal, 2024). This skills gap limits the extent to which BDA can be fully leveraged, thereby creating a disconnect between technological capability and organizational capacity. Furthermore, organizational resistance to data-driven cultures and the inertia of traditional decision-making practices can hinder BDA adoption.

Beyond internal organizational challenges, systemic issues also impede the optimal use of BDA. For instance, the fragmentation of data across multiple systems often results in silos that inhibit data integration and holistic analysis (Udegbe et al., 2019; Mowrer et al., 2017). This segmentation not only hampers real-time insight generation but also compromises the comprehensiveness of data-driven decisions. When data cannot be synthesized across platforms, the resulting analyses are often piecemeal and potentially misleading, undermining the reliability of conclusions drawn (Pawar & Dhumal, 2024; Zhu et al., 2016).

A further limitation in the existing literature is its narrow sectoral and geographical focus. Much of the current research tends to concentrate on specific industries, particularly healthcare and energy, with limited exploration of BDA's impact in other vital sectors such as agriculture, public administration, or education (Kumar & Singh, 2019; Sugumaran et al., 2017). Similarly, geographical scope is often constrained, with most studies based in high-income countries. This raises concerns about the generalizability of findings and highlights the need for broader research that encompasses diverse contexts and economies (Naik et al., 2022; Tripathi et al., 2024).

To address these gaps, the present narrative review aims to examine the current state of BDA applications for decision support, with a focus on identifying critical techniques, tools, and sector-specific implementations. The review seeks to synthesize empirical findings across industries and geographies to provide a holistic understanding of BDA's role in enhancing decision-making. By doing so, it endeavors to bridge the conceptual and practical divides in the existing literature and offer insights into how BDA can be more effectively leveraged in varied organizational contexts.

This review is particularly focused on synthesizing studies that address BDA implementation across sectors such as healthcare, manufacturing, logistics, and energy, with selective inclusion of emerging applications in agriculture and public service. Geographically, the analysis aims to incorporate perspectives from both developed and developing regions to highlight contextual variations and commonalities. Such breadth is essential for drawing conclusions that are both evidence-based and context-sensitive, thereby informing future research and practical applications.

This study is motivated by the need to identify research gaps in the operationalization of Big Data Analytics (BDA) for organizational decision-making. Specifically, it investigates enabling and constraining factors of BDA adoption and synthesizes cross-sectoral evidence to advance discourse on data-informed governance in the digital era.

METHOD

This study adopts a systematic narrative review methodology to examine the application of Big Data Analytics (BDA) in enhancing decision support systems across various industries. The methodological approach undertaken in this review aims to provide a comprehensive synthesis of empirical evidence, theoretical insights, and technological developments associated with BDA implementation in decision-making contexts. The methodology is structured around five main components: literature database selection, keyword formulation, inclusion and exclusion criteria, types of studies included, and the selection and evaluation process of the retrieved literature.

The literature for this review was gathered from multiple scholarly databases that have been recognized for their credibility, comprehensiveness, and relevance to the domains of computer science, engineering, business intelligence, and interdisciplinary applications. Scopus was utilized as the primary source due to its broad coverage of peer-reviewed articles, conference proceedings, and citation tracking features. Scopus has been widely used in systematic literature reviews because of its robust indexing capabilities and analytical tools, making it highly suitable for mapping the influence and progression of BDA-related research over time (El-Helw et al., 2015). Complementing Scopus, IEEE Xplore was also selected given its specialization in engineering and technological innovation. The database is particularly valuable for identifying advanced BDA frameworks, algorithms, and data processing tools emerging from disciplines such as information systems and computer engineering (Sugumaran et al., 2017). In order to capture a wider range of scholarly contributions, including grey literature, dissertations, and institutional reports, Google Scholar was employed as an auxiliary source. Although Google Scholar provides expansive coverage, it necessitates rigorous screening of article quality, as it includes both peer-reviewed and non-peer-reviewed sources, requiring researchers to verify credibility through manual assessment of journal impact, citation metrics, and author affiliation.

To identify relevant literature, a set of carefully constructed keyword combinations was developed based on Boolean logic. The search strategy was informed by prior studies and expert recommendations in the field of big data and analytics. Key search terms included: "Big Data Analytics" AND "Decision Support"; "Big Data" AND "Techniques" AND "Tools"; "Big Data" OR "Big Data Analytics" AND "Applications" AND "Industry"; "Healthcare" AND "Big Data" AND "Analytics"; and "Predictive Analytics" AND "Decision Making" AND "Business Intelligence." These combinations were selected to maximize retrieval of studies focused on BDA applications in organizational decision-making. To refine the scope further, domain-specific keywords such as "energy," "manufacturing," "logistics," and "healthcare" were appended to the core terms to ensure coverage of industry-specific implementations. The iterative use of such keywords across databases helped ensure both breadth and depth in the literature retrieval process, aligning with the aim of developing a cross-sectoral synthesis (Redondo et al., 2020; Kumar & Singh, 2019).

The inclusion and exclusion criteria were defined a priori to maintain transparency and consistency in article selection. Only peer-reviewed journal articles, conference proceedings, and academic book chapters published in English between 2010 and 2024 were included in this review. The timeframe was chosen to capture the contemporary developments in BDA technology and its applications in decision-making environments. Studies were considered eligible if they explicitly addressed the use of BDA for supporting decision-making processes, either through conceptual frameworks, empirical analyses, or case studies. Articles that provided methodological innovation in BDA tools or techniques relevant to decision support were also included. Conversely, articles that solely focused on data architecture, storage solutions, or hardware infrastructure without connecting these to decision-making applications were excluded. Similarly, opinion pieces, editorials, and short communications lacking empirical evidence or methodological rigor were filtered out during the screening phase.

This review encompasses a range of research designs and publication types to ensure a balanced and nuanced understanding of the topic. The types of studies included span from experimental research and quasi-experimental evaluations to descriptive case studies and exploratory qualitative analyses. Randomized controlled trials, though less common in BDA research, were also reviewed where available, particularly in sectors such as healthcare where predictive analytics are deployed in clinical decision-making. Moreover, design science research and simulation-based modeling studies were included to account for methodological diversity in the development and validation of BDA tools. This heterogeneity in study design is reflective of the interdisciplinary nature of BDA, which intersects with fields ranging from computer science and engineering to management and public administration.

The process of literature selection involved multiple phases of screening and quality assessment to ensure the relevance and reliability of the selected articles. Initially, search results from each database were exported and compiled into a reference management system. Duplicates were removed to streamline the corpus. Titles and abstracts were then screened manually to evaluate thematic alignment with the research objectives. Articles that passed this stage were subjected to full-text review to assess their methodological soundness, clarity of BDA application, and contribution to understanding decision-making processes. During this phase, particular attention was paid to the context of BDA application, including industry sector, geographical location, and the type of decision being supported. Articles that did not meet the inclusion criteria or failed to provide sufficient methodological detail were excluded.

To ensure rigor in data extraction and thematic synthesis, a coding protocol was established. Each article was analyzed based on predefined categories including: BDA techniques used (e.g., machine learning, predictive analytics), tools or platforms implemented (e.g., Hadoop, Spark, visualization software), sector of application, type of data analyzed (structured, unstructured), decision context (strategic, operational, or tactical), and reported outcomes. This structured approach facilitated the identification of thematic patterns across studies and enabled the construction of an integrative framework to be discussed in the results section.

In summary, the methodology employed in this narrative review is anchored in systematic literature search procedures, transparent selection criteria, and rigorous screening protocols. By drawing on diverse databases, employing well-crafted keyword strategies, and incorporating a wide range of study designs, the review aims to provide a comprehensive and credible synthesis of how Big Data Analytics is being utilized to support decision-making across industries. The methodological choices reflect an intentional effort to capture both the depth and breadth of BDA applications, offering valuable insights into technological trends, implementation challenges, and sector-specific innovations.

RESULT AND DISCUSSION

The narrative review of existing literature on Big Data Analytics (BDA) reveals a diverse and rapidly evolving field marked by significant applications across industries, varied analytical techniques, and context-dependent factors influencing its success. This section presents the key findings organized into four thematic categories: analytical techniques, technological tools, sectoral applications, and enabling organizational conditions.

A. Analytical Techniques in Big Data Analytics

The literature highlights three major BDA techniques that support decision-making: (1) data mining for uncovering hidden patterns, (2) predictive analytics for forecasting trends, and (3) machine learning for processing unstructured data and enhancing prediction accuracy.. Data mining serves as a foundational technique for uncovering previously unidentified patterns within large datasets. It is particularly effective in clustering and classifying information for strategic insights. For example, Tripathi et al. (2024) and Kumar and Singh (2019) emphasized the ability of data mining to streamline data exploration processes, enabling organizations to extract value from datasets that would otherwise remain unutilized. Empirical evidence supports the assertion that data mining improves productivity by informing strategic choices previously unreachable through traditional methods.

Predictive analytics, on the other hand, is increasingly employed to anticipate future trends based on historical data. This approach has proven especially useful in customer behavior modeling, risk assessment, and strategic forecasting. Kumar and Singh (2019) report that predictive analytics yields improved decision accuracy, contributing to significant returns on investment, particularly in health care and business contexts. Similarly, Udegbe et al. (2019) affirm that organizations implementing predictive models experience enhanced operational efficiency and responsiveness.

Machine learning emerges as a dominant paradigm in BDA, particularly for processing unstructured data such as text and images. Algorithms including regression, decision trees, and neural networks are utilized for automated decision-making. According to Naik et al. (2022), machine learning not only elevates the speed of analysis but also achieves superior prediction accuracy compared to traditional statistical methods, especially in fields like medical diagnostics and fraud detection. The literature consistently highlights the scalability and adaptability of machine learning algorithms in dynamic and data-intensive environments.

B. Technological Tools and Platforms

The effective deployment of BDA is contingent on the selection and integration of appropriate technological tools. Apache Hadoop remains a cornerstone framework for distributed data storage and processing. Tripathi et al. (2024) and Udegbe et al. (2019) note Hadoop's robustness in handling heterogeneous data formats at scale. However, they also highlight its operational complexity, necessitating skilled infrastructure management and technical oversight.

Apache Spark has gained favor for its in-memory data processing capabilities, which offer significant speed advantages over Hadoop. Spark's compatibility with multiple programming languages and support for real-time analytics make it suitable for high-velocity environments. Redondo et al. (2020) underscore Spark's utility in time-sensitive decision-making processes, though they caution about potential memory management issues that could affect stability.

Data visualization tools such as Tableau are also widely adopted for presenting complex analytical results in accessible formats. According to Anand and Babu (2025), Tableau enables decision-makers to interact with data through dynamic dashboards, promoting deeper engagement with insights. Its limitations, however, include high licensing costs that may deter adoption among small and medium enterprises. Overall, the literature indicates that the strategic alignment of tools with organizational capabilities is critical to the successful implementation of BDA.

C. Applications Across Industry Sectors

The application of BDA spans multiple industries, with significant impact documented in healthcare, manufacturing, logistics, and energy. In the healthcare sector, BDA supports clinical decision-making by aggregating and analyzing patient data from electronic health records. Naik et al. (2022) emphasize the use of BDA in disease surveillance and population health management, facilitating early diagnosis and tailored treatment plans. Kumar and Singh (2019) further note that hospitals employing predictive analytics report reductions in hospital readmissions and improved patient satisfaction.

In manufacturing, BDA is utilized to optimize production processes and promote sustainable operations. Tripathi et al. (2024) detail how data analytics enables real-time monitoring of production lines, identification of inefficiencies, and implementation of green manufacturing strategies. This data-driven approach helps organizations enhance productivity while simultaneously reducing environmental impact.

The logistics sector leverages BDA to streamline supply chain management. Tools for demand forecasting, route optimization, and inventory control enable firms to reduce operational costs and improve delivery performance. Udegbe et al. (2019) observe that logistics firms using BDA are more responsive to market fluctuations and better equipped to maintain service levels in volatile conditions.

In the energy sector, BDA plays a role in infrastructure monitoring and resource optimization. Zhu et al. (2016) highlight applications in real-time monitoring of gas pipelines and predictive maintenance of energy grids. Such implementations enhance both safety and efficiency, reducing downtime and improving resource allocation.

Cross-national and cross-sectoral comparisons reveal variability in the effectiveness of BDA implementation. Countries with advanced digital infrastructure, such as Japan and Canada, demonstrate higher adoption rates and more mature use cases. Tripathi et al. (2024) indicate that national policy support, such as subsidies for digital innovation, correlates with increased organizational readiness and technological integration.

Sectoral comparisons show that healthcare organizations tend to realize quicker cost reductions and outcome improvements due to BDA, compared to traditional sectors like agriculture or construction, where digital transformation is less advanced (Kumar & Singh, 2019). This disparity underscores the need for context-sensitive strategies to guide BDA adoption.

D. Determinants of Successful Implementation

The success of BDA deployment depends on multiple organizational and technical factors. Data quality is a recurrent theme in the literature, with poor data integrity identified as a significant barrier to effective analytics. Protopsaltis et al. (2020) argue that high-quality data is essential to ensure reliable outputs from analytical models. Inconsistent or incomplete data can mislead decision-makers and undermine the credibility of data-driven strategies.

Human capital is equally critical. Pawar and Dhumal (2024) stress the importance of skilled personnel in bridging the gap between data insights and organizational action. Redondo et al. (2020) highlight the increasing demand for professionals proficient in data science, programming, and domain-specific analytics. A well-trained workforce enables organizations to interpret complex outputs and integrate them into actionable strategies.

Organizational culture also plays a pivotal role. Institutions that encourage data-driven decision-making and foster innovation are more likely to benefit from BDA implementation. Pawar and Dhumal (2024) suggest that leadership commitment and interdepartmental collaboration are key enablers of successful analytics integration. Without a supportive culture, even the most advanced analytical tools may remain underutilized.

The interplay between data quality and human capital is particularly noteworthy. Tripathi et al. (2024) posit that skilled analysts are better equipped to identify and correct data anomalies, thereby enhancing the overall reliability of the analytics process. Conversely, high-quality data amplifies the effectiveness of competent analysts, creating a virtuous cycle that strengthens decision support capabilities. Udegbe et al. (2019) and Protopsaltis et al. (2020) similarly affirm that investments in both human resources and data governance yield superior analytical outcomes.

Taken together, the findings suggest that optimizing these enabling conditions is essential for maximizing the impact of BDA in industrial decision-making. Success is contingent not merely on technological adoption, but on the alignment of infrastructure, talent, and institutional values. As organizations seek to leverage big data for strategic advantage, a holistic approach that integrates tools, people, and processes emerges as the most effective pathway to sustainable implementation.

The present review builds upon and extends the existing literature on Big Data Analytics (BDA) in decision support systems by offering a more comprehensive and sector-diverse perspective on its applicability and effectiveness. Prior studies have predominantly focused on specific sectors such as healthcare, as noted by Kumar and Singh (2019), emphasizing the role of BDA in improving diagnostic accuracy and patient management. This review, however, reveals broader applications across industries such as manufacturing, logistics, and energy, highlighting how BDA enhances efficiency, supports real-time analytics, and contributes to sustainable practices in diverse organizational settings. These findings affirm the transformative role of BDA in a wide range of decision-making contexts, reinforcing its growing significance in the data-driven economy.

At the same time, this review uncovers several challenges that previous studies have only partially addressed. Issues surrounding data quality and integration, the availability of skilled personnel, and organizational culture emerge as critical barriers to effective BDA implementation. Redondo et al. (2020) stress that despite advances in technology, organizational readiness remains uneven, with many institutions lacking the infrastructure and human capital needed to fully leverage big data. Thus, while the technological potential of BDA is widely acknowledged, its practical adoption continues to be constrained by systemic and structural factors.

Systemic barriers are particularly salient in the context of regulatory constraints and infrastructural limitations. For instance, stringent data protection laws, particularly in healthcare, pose significant challenges to the integration and analysis of large-scale patient data. Tripathi et al. (2024) argue that while these regulations are essential for safeguarding individual privacy, they can inadvertently hinder innovation and data-driven decision-making. This tension underscores the need for balanced data governance frameworks that both protect personal data and facilitate responsible analytics.

Moreover, the digital divide remains a major obstacle, especially in developing economies where IT infrastructure is often inadequate. Protopsaltis et al. (2020) illustrate that without stable internet connectivity, cloud-based analytics, and robust data storage systems, organizations struggle to maintain real-time data processing capabilities. Consequently, the benefits of BDA are disproportionately accessible to institutions in technologically advanced regions, leading to global disparities in data-driven decision support.

Another systemic issue identified in the literature is the siloed nature of organizational data systems. Mowrer et al. (2017) observe that when departments within an organization operate independently without integrated data-sharing mechanisms, it severely limits the value of BDA. Fragmented data sources not only hinder comprehensive analysis but also delay the generation of actionable insights. Addressing this requires a cultural shift towards greater interdepartmental collaboration and the adoption of integrated data architectures.

In response to these challenges, the literature offers several strategic solutions. One widely supported approach is the development of flexible data policies. Tripathi et al. (2024) advocate for policy frameworks that evolve in tandem with technological advancements, allowing organizations to navigate the complex terrain of data privacy without stifling innovation. Such policies should be adaptive, context-sensitive, and regularly reviewed to remain relevant in an era of rapid data proliferation.

Investments in IT infrastructure also feature prominently as a solution in the academic discourse. Anand and Babu (2025) suggest that modernizing hardware and software systems, along with implementing efficient cloud technologies, can significantly enhance an organization's ability to manage and analyze big data. This not only facilitates real-time decision-making but also ensures scalability and data security in an increasingly complex digital environment.

Capacity building through human resource development is another critical area. Redondo et al. (2020) emphasize the importance of continuous training programs aimed at equipping employees with the necessary analytical and technical skills to navigate big data environments. Organizations must invest in both formal education and on-the-job training to cultivate a workforce capable of extracting value from complex data sets.

The review also highlights the role of organizational culture in shaping the success of BDA initiatives. Pawar and Dhumal (2024) point out that organizations that foster a data-driven mindset across all levels of management are more likely to integrate BDA into their strategic decision-making processes. This cultural orientation towards evidence-based decision-making enhances organizational agility and responsiveness in dynamic markets.

Globally, the implementation of BDA varies considerably across countries and industries, as revealed in the comparative analysis. Nations with strong technological policies and robust digital ecosystems, such as Japan and Canada, demonstrate more advanced BDA adoption rates. Tripathi et al. (2024) show that these countries benefit from coordinated national strategies that support digital transformation through funding, education, and policy alignment. In contrast, developing countries often face fragmented efforts and lack the institutional support needed for sustainable BDA integration.

Sectoral differences are equally noteworthy. For example, while healthcare organizations report significant returns on investment from BDA in terms of improved patient outcomes and reduced costs, traditional industries such as agriculture and construction have been slower to adopt these technologies. This discrepancy reflects varying levels of technological readiness and sector-specific barriers, including capital constraints, regulatory hurdles, and limited access to data.

While the present review offers valuable insights into the current landscape of BDA for decision support, it also acknowledges several limitations. Much of the existing research remains concentrated in specific regions and industries, which restricts the generalizability of the findings. Moreover, there is a lack of longitudinal studies examining the sustained impact of BDA over time. Most studies provide snapshots of implementation without exploring long-term outcomes or organizational transformation.

Another limitation concerns the measurement of BDA effectiveness. There is no universally accepted framework for evaluating the success of BDA initiatives, leading to inconsistencies in reported outcomes. Future research should aim to develop standardized metrics that capture both quantitative and qualitative dimensions of BDA performance, including user satisfaction, decision quality, and organizational learning.

Furthermore, the rapid evolution of big data technologies necessitates ongoing research to keep pace with emerging trends. As new tools and techniques are developed, their implications for decision-making must be critically assessed. This includes exploring the ethical dimensions of BDA, particularly in areas such as algorithmic bias, data ownership, and transparency. Addressing these concerns will be essential for building trust and legitimacy in data-driven decision systems.

In sum, while BDA offers immense promise for enhancing decision-making across sectors, its successful implementation hinges on addressing systemic challenges, aligning policy and practice, and fostering an organizational culture that values data as a strategic asset. These efforts must be supported by robust infrastructure, skilled human capital, and a commitment to continuous learning and innovation. Further empirical investigation is essential to refine our understanding of how BDA can be most effectively deployed to meet the evolving needs of organizations in a data-rich world.

CONCLUSION

This narrative review highlights the critical role of Big Data Analytics (BDA) in supporting evidence-based decision-making across various industries. The analysis reveals that techniques such as data mining, predictive analytics, and machine learning significantly contribute to more accurate, efficient, and timely decisions, particularly in healthcare, manufacturing, logistics, and energy sectors. The use of platforms like Apache Hadoop, Apache Spark, and Tableau facilitates real-time analysis and visualization of large data sets, albeit with challenges related to complexity, cost, and required expertise. Organizational factors such as data quality, human resource competency, and innovation-oriented culture emerged as fundamental to successful BDA implementation.

Despite these benefits, the review uncovers persistent systemic and structural barriers. These include regulatory constraints, infrastructural limitations, and organizational silos that hinder data integration and effective use. Such issues call for responsive policy development, technological investment, and human capital enhancement. The urgency to address these barriers is particularly pronounced in developing countries, where BDA implementation remains limited.

To overcome these challenges, strategic interventions are recommended, including adaptive data governance, investment in cloud-based infrastructure, and capacity-building initiatives for data professionals. Future research should explore longitudinal case studies and sector-specific implementations of BDA, especially in underrepresented regions and industries. Enhancing access, education, and awareness remains a vital strategy to unlock BDA's transformative potential in driving sustainable and data-driven development worldwide.

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