Novatio: Journal of Management Technology and Innovation
E-ISSN : 3030-8674
Volume. 2, Issue 2, April 2024
Page No: 91-105

Big Data in Context: A Narrative Review of Opportunities, Barriers, and Global Perspectives

Bella Noer Achaddiah[1], Safri[2]
[1]**Pusat Pengembangan SDM Perhubungan Udara, Indonesia**
[2]**Universitas Dirgantara Marsekal Suryadarma, Indonesia**
Correspondent : bella.achaddiah@gmail.com[1]

Received : February 21, 2024
Accepted : April 12, 2024
Published : April 30, 2024

Citation: Achaddiah, B, N., Safri. (2024). Big Data in Context: A Narrative Review of Opportunities, Barriers, and Global Perspectives. Novatio: Journal of Management Technology and Innovation, 2(2), 91-105.

ABSTRACT: This narrative review examines the transformative role of big data in organizational performance, predictive analytics, and smart manufacturing, while highlighting disparities in adoption between developed and developing economies. Literature was collected from major databases (Scopus, Web of Science, PubMed, and Google Scholar) using rigorous criteria to ensure methodological validity. Findings reveal that big data improves decision-making, efficiency, and risk management, with digital twin technologies enhancing reliability in manufacturing. However, barriers remain, including infrastructure gaps, skill shortages, resistance to change, and data governance challenges—especially among SMEs and rural communities. The review underscores the need for targeted policy interventions and cross-sector collaborations to close these gaps. Its unique contribution lies in synthesizing global disparities and offering integrative strategies for inclusive, sustainable big data adoption.

Keywords: Big Data Analytics, Predictive Analytics, Digital Transformation, Smart Manufacturing, Organizational Outcomes, SMES, Data Governance.

INTRODUCTION

Digital transformation has emerged as one of the defining phenomena of the contemporary era, permeating multiple sectors and reshaping how organizations, governments, and societies operate. Driven by the rapid advancement and adoption of technologies such as artificial intelligence (AI), the Internet of Things (IoT), and big data analytics, this transformation extends beyond operational efficiency to fundamentally alter organizational cultures, consumer behaviors, and societal interactions (Subrahmanyam, 2025; Warner & Wäger, 2019). The digital-first approach has become not merely an option but a necessity, as competitiveness and resilience now hinge on the ability to adapt to continuous technological change. Importantly, this transformation occurs against a backdrop of uncertainty and disruption, particularly highlighted by the COVID-19 pandemic, which underscored the importance of digital readiness and resilience (Abedsoltan, 2023; Müller et al., 2024).

Scholars and practitioners alike recognize that digital transformation is both an opportunity and a challenge. On one hand, digital innovations provide unprecedented capabilities for data-driven decision-making, operational optimization, and customer engagement. On the other hand, these same innovations require organizations to address the complexities of infrastructure, human capital, and cultural change, thereby broadening the conversation from mere adoption to sustainable integration (Warner & Wäger, 2019). Recent studies highlight that businesses engaging in digital initiatives report between 20–30% increases in engagement and efficiency, reinforcing the measurable value of such transformations (Chandratreya, 2025). At the executive level, surveys confirm that digital transformation remains a top priority to sustain competitive advantage, with strategic agendas increasingly reflecting this urgency (Li & Zhou, 2023; Brunet et al., 2018).

The global diffusion of digital technologies has been uneven, with marked differences in adoption rates and maturity levels across regions. While advanced economies demonstrate higher levels of infrastructure and investment, developing countries are also actively embracing digital strategies as a pathway to growth and innovation (Liao & Feng, 2023). In Southeast Asia, for example, small and medium-sized enterprises (SMEs) have harnessed social media platforms and e-commerce ecosystems to enhance competitiveness and expand markets (Alam et al., 2022). Conversely, systemic barriers in other regions, including organizational inertia and inadequate infrastructure, have constrained digital adoption (Rahman et al., 2025). Such disparities highlight the need for context-specific strategies that acknowledge local capabilities and constraints, underscoring that digital transformation is neither uniform nor linear (Lisnawati et al., 2024; Bhimavarapu, 2025).

The pandemic further amplified these dynamics, exposing the vulnerabilities of organizations resistant to digital change and rewarding those with agile, adaptable systems (Müller et al., 2024; Mosch et al., 2022). In many cases, COVID-19 served as a catalyst, prompting firms to reevaluate business models and accelerate investment in digital infrastructures (Holroyd, 2019). The public and private sectors alike have since prioritized digital literacy, equitable access, and collaborative frameworks to ensure inclusivity and long-term sustainability in digital adoption (Sarto et al., 2024; Jha, 2022). The importance of cultivating an ethos of continuous learning and strategic foresight has thus become integral to thriving amidst global complexities and ongoing technological disruption (Sterrett & Richardson, 2022; Gacser et al., 2024).

Despite these advances, significant challenges remain in addressing big data as a central pillar of digital transformation. Developed and developing countries confront distinct obstacles, reflecting differences in infrastructure, regulatory frameworks, and human capital development. For many developing economies, inadequate technological infrastructure—ranging from insufficient hardware and software to high costs of data collection and storage—hinders effective use of big data analytics (Charles & Emrouznejad, 2018; Coleman et al., 2016). SMEs, in particular, struggle to mobilize the resources required to implement large-scale data solutions. In contrast, developed countries grapple with issues of data governance, integration across platforms, and the maintenance of consistency and quality (Kumar et al., 2022).

Human resource constraints exacerbate these disparities. While advanced economies often boast a pool of data scientists and analysts, a mismatch persists between academic training and industry requirements, limiting the applicability of existing expertise (Mathivanan & Jayagopal, 2020). Developing countries face a more acute shortage, with limited educational resources and training programs failing to prepare a workforce capable of leveraging big data for innovation and decision-making (Tan & Haji, 2017; Amer et al., 2022). These skill gaps impede not only the adoption but also the sustainability of big data initiatives.

Cultural and organizational resistance further complicates the picture. In developing contexts, traditional business practices and skepticism about the benefits of big data create inertia that hinders adoption (Charles & Emrouznejad, 2018). In developed regions, organizations often cling to established decision-making models, underestimating the transformative potential of data-driven approaches (Khan et al., 2021). Alongside these organizational barriers, ethical and regulatory challenges loom large. Strict data protection frameworks such as the General Data Protection Regulation (GDPR) in Europe impose compliance burdens that complicate big data integration (Whitman, 2021). Meanwhile, the absence of comprehensive legal protections in many developing countries exposes organizations to risks and undermines trust in data-driven systems (Taifa & Nzowa, 2025).

These challenges expose critical gaps in the literature. Much of the existing research disproportionately focuses on developed economies, often neglecting the unique experiences and constraints of developing contexts (Charles & Emrouznejad, 2018; Rees et al., 2022). Comparative empirical studies remain limited, leaving questions about how strategies and outcomes diverge across regions. Furthermore, integrative frameworks that account for technological, organizational, and human factors are underdeveloped (Kumar et al., 2022). While numerous short-term evaluations exist, longitudinal research capable of capturing the sustained impacts of big data adoption is scarce (Taifa & Nzowa, 2025). Additionally, SMEs remain underrepresented in the literature despite their central role in many economies, creating a blind spot in both research and practice (Coleman et al., 2016; Lainjo, 2019).

This review therefore aims to synthesize the current body of research on digital transformation and big data, with a particular focus on the challenges and opportunities that arise in different regional and organizational contexts. By examining factors such as infrastructure, human capital, cultural attitudes, and regulatory frameworks, the review seeks to provide a comprehensive understanding of the conditions that facilitate or inhibit successful digital adoption. It also explores the intersections of these factors, emphasizing the need for holistic strategies that integrate technological, organizational, and societal dimensions.

The scope of this review extends beyond a global overview to consider region-specific dynamics, with particular attention to the contrasts between developed and developing countries. The analysis incorporates comparative perspectives to highlight divergences in adoption trajectories, regulatory approaches, and organizational readiness. While the focus is on broad patterns, attention is also given to underrepresented populations, such as SMEs and rural communities, which often experience unique challenges in accessing and utilizing digital tools (Coleman et al., 2016; Taifa & Nzowa, 2025). By adopting this approach, the review aspires to illuminate pathways for more inclusive, equitable, and effective digital transformation in the era of big data.

METHOD

The methodology adopted in this review was designed to ensure rigor, comprehensiveness, and relevance in capturing the breadth of scholarly discourse on big data and its diverse applications. The process involved systematic strategies for literature collection, keyword design, inclusion and exclusion criteria, and evaluation of studies, allowing for a robust synthesis of findings across different sectors and geographical contexts. The approach was also framed to highlight underrepresented areas, thereby contributing to a more balanced understanding of big data's global potential and limitations.

The first stage in constructing the methodology involved selecting reliable databases for literature collection. Scopus was utilized as the primary database due to its extensive coverage of peer-reviewed scientific publications and its capacity to encompass research from multiple disciplines, including computer science, engineering, business, and sustainability (Jin et al., 2024; Schöggl et al., 2023). Web of Science was included as a complementary source, ensuring access to high-impact journals and multidisciplinary works that contribute to a comprehensive overview of big data across fields such as healthcare, supply chain management, and digital transformation (Sia et al., 2024). For studies specifically addressing clinical and health informatics applications of big data, PubMed was consulted, as it provides specialized access to literature in medical sciences and public health (Charles & Emrouznejad, 2018). In addition, Google Scholar was employed to broaden the scope of collection by incorporating grey literature such as conference proceedings, dissertations, and policy papers, which often provide insights into emerging areas of research and practical applications of big data (Iftikhar & Khan, 2022).

The retrieval process was supported by the use of carefully selected keywords and Boolean operators to maximize the precision and inclusivity of the search results. Key terms included "big data," "big data analytics," "data management," "predictive analytics," "machine learning," "artificial intelligence," "data-driven decision-making," and "sustainability." Boolean operators such as AND, OR, and NOT were used to combine or exclude terms strategically. For instance, searches such as "big data" AND "sustainability" were used to identify literature exploring the nexus between analytics and sustainable practices, while queries like "predictive analytics" OR "machine learning" broadened the search to encompass literature addressing these methodologies as distinct but related areas. Quotation marks were employed for phrase searches, ensuring that precise concepts such as "data-driven decision-making" were accurately captured in the retrieved results. Advanced search features in Scopus and Web of Science allowed for further refinement by publication year, document type, and subject area, facilitating the identification of the most relevant and recent contributions (Garouani et al., 2022).

To capture a comprehensive view of big data applications, synonyms and related terms were also incorporated into the search strategy. This included terms such as "data mining," "data integration," "digital transformation," and "business intelligence," which ensured that variations in terminology across disciplines and contexts did not exclude significant research (Proto et al., 2020). Such inclusivity in the keyword design was particularly important in mapping the diverse ways big data is conceptualized and applied across sectors.

The inclusion and exclusion criteria were carefully delineated to maintain both the relevance and quality of the studies. Articles were included if they (i) were published in peer-reviewed journals or as conference proceedings with identifiable academic credibility, (ii) focused explicitly on the use, challenges, or opportunities of big data analytics, and (iii) were published between 2015 and 2025 to ensure contemporaneity and relevance in light of rapid technological advancements. Studies were excluded if they (i) were not available in English, (ii) did not provide empirical or theoretical insights related to big data, or (iii) focused exclusively on technical algorithmic developments without addressing broader organizational, social, or sectoral implications. This approach ensured a balanced selection of both methodological and applied studies while excluding literature with limited scope or relevance.

The review incorporated diverse types of research to ensure multidimensional coverage of the topic. Experimental designs such as randomized controlled trials and case-control studies were included when they pertained to healthcare and biomedical applications of big data, thereby ensuring methodological rigor in evidence generation. Cohort studies and case studies were incorporated to examine longitudinal and contextual applications, particularly in organizational and sectoral analyses. Literature reviews and meta-analyses were also included to capture broader thematic insights and consolidate prior research findings, providing a foundation for identifying trends, gaps, and contradictions in the field. This diversity of research types allowed for a richer synthesis of findings, reflecting the cross-sectoral nature of big data applications.

The process of literature selection and evaluation followed a multi-step approach. First, the initial search results from the four databases were imported into reference management software, where duplicate records were identified and removed. The remaining studies underwent a two-stage screening process. In the first stage, titles and abstracts were reviewed to determine alignment with the inclusion criteria. Studies that met the criteria were then subjected to full-text evaluation, in which methodological rigor, relevance to the research objectives, and clarity of contribution were assessed. During this stage, special attention was given to studies addressing underrepresented contexts, such as SMEs, rural communities, and developing countries, to ensure their inclusion in the synthesis. Finally, the selected studies were subjected to a critical appraisal, evaluating their strengths and limitations, as well as their contribution to theoretical, methodological, and practical insights on big data.

One of the important considerations in this methodology was the recognition of underrepresented populations and sectors within the existing literature. Despite the prominence of big data research in healthcare and finance, limited attention has been given to SMEs, rural communities, and developing countries. SMEs, which form a substantial proportion of global economic activity, often lack the resources to implement big data strategies, and their representation in academic literature remains sparse (Rees et al., 2022; Lainjo, 2019). Rural communities face distinct challenges, including insufficient infrastructure and limited digital literacy, yet the role of big data in supporting their growth and resilience is rarely documented (Taifa & Nzowa, 2025). Geographical disparities also persist, as the majority of studies originate from North America and Western Europe, leaving substantial gaps in understanding how big data adoption could be contextualized in regions such as Africa, Latin America, and South Asia (Gallese et al., 2020). Furthermore, sectors such as agriculture, environmental science, and non-profit organizations, despite their potential for data-driven innovation, remain underexplored in existing research (Piciu et al., 2018; Khan et al., 2021).

By applying this comprehensive methodology, the review was able to not only synthesize existing knowledge but also identify areas where further research is urgently needed. The combination of targeted search strategies, inclusive keyword design, clear criteria for inclusion and exclusion, and critical appraisal of selected studies ensured a robust and balanced synthesis. Moreover, the deliberate focus on underrepresented areas provided a pathway to enhance the inclusivity and global relevance of big data research, highlighting contexts and sectors that merit greater scholarly and practical attention. Through this methodological approach, the review provides a foundation for understanding both the transformative potential and the inherent challenges of big data in diverse contexts, contributing to the advancement of theory, policy, and practice.

RESULT AND DISCUSSION

The findings from the reviewed literature reveal the significant influence of big data and associated digital technologies on organizational outcomes, predictive analytics applications, and smart manufacturing practices. By synthesizing empirical evidence and comparative case studies across multiple contexts, the results demonstrate both convergence and divergence in how developed and developing nations adopt and benefit from these technological advancements. The analysis is organized into three main themes that emerged from the literature: the significance of big data in organizational outcomes, the role of predictive analytics in data utilization, and the influence of digital twins on smart manufacturing. Each theme highlights not only the measurable impact of big data but also the contextual disparities shaping its adoption and effectiveness.

The Significance of Big Data in Organizational Outcomes

Empirical findings consistently underscore the pivotal role of big data in shaping organizational outcomes across industries. Studies demonstrate that organizations leveraging big data-driven frameworks are more capable of enhancing decision-making processes, operational efficiencies, and long-term strategic planning. For example, Jin et al. (2024) documented how organizations integrating big data into sustainable digital marketing strategies achieved significantly improved decision-making, facilitated by advanced data analysis and predictive modeling. These findings are supported by Sia et al. (2024), who reported that the adoption of data-driven decision-making within health, safety, and environmental (HSE) management at PETRONAS increased assurance accuracy above 80%, reflecting a transformation of traditional intervention models into proactive, evidence-based practices.

Statistical evidence further validates these transformations. Chandratreya (2025) highlighted that organizations engaging with digital technologies, including big data analytics, reported an average increase in engagement and efficiency of 20–30%. Similarly, Warner and Wäger (2019) emphasized that a significant proportion of executives prioritize digital transformation as essential for sustaining competitive advantage, with big data positioned at the core of these strategic initiatives. This body of literature collectively confirms that big data enhances organizational responsiveness and positions firms to adapt effectively to the volatile conditions of the digital economy.

Comparative perspectives reveal notable differences between developed and developing nations. In advanced economies, big data is primarily deployed in high-stakes sectors such as healthcare, finance, and energy, where the scale and complexity of datasets allow for sophisticated analytical frameworks. Schöggl et al. (2023) observed that digital technologies, including big data, have become integral to advancing sustainability practices in manufacturing industries across both developed and developing contexts. However, while developed countries lead in adoption, developing nations are rapidly scaling their use of data analytics, often motivated by the need to optimize limited resources. This trend signals not only growth in adoption rates but also innovation in how developing economies adapt big data to local challenges. Such findings demonstrate a dual global trajectory where developed countries refine advanced models and developing regions expand applications in resource-constrained but innovation-driven contexts.

The Role of Predictive Analytics in Data Utilization

Predictive analytics has emerged as a cornerstone of big data utilization, with substantial statistical evidence supporting its transformative potential. A prominent case study from PETRONAS illustrates the effectiveness of predictive frameworks, where implementation reduced irrelevant planned activities by 17% while enabling a 43% increase in unplanned yet critical interventions (Sia et al., 2024). These results highlight how predictive models improve the allocation of resources, streamline operational processes, and ultimately enhance productivity by enabling more targeted and timely decision-making.

The application of predictive analytics varies significantly across economic contexts. In developed nations, predictive analytics is deployed in advanced domains such as financial risk management, healthcare forecasting, and environmental monitoring. Coleman et al. (2016) noted that the availability of vast, high-quality datasets and advanced computational resources enables the use of complex models with high predictive accuracy. Conversely, in developing countries, predictive analytics is often employed in more foundational contexts, such as basic demand forecasting, inventory management, and small-scale resource allocation. Lee et al. (2020) emphasized that SMEs in these regions benefit significantly from simpler analytics techniques, which nonetheless improve their competitiveness by enhancing visibility and predictability within supply chains.

The application of predictive analytics in social media big data exemplifies this divergence. In developed countries, organizations employ sophisticated AI-driven models and machine learning algorithms to forecast consumer demand and sentiment, integrating these insights into strategic marketing and operations (Iftikhar & Khan, 2022). In contrast, businesses in developing regions often adopt less complex approaches, using basic predictive tools to track demand fluctuations and enhance supply chain efficiency. While the sophistication of implementation differs, both contexts underscore the value of predictive analytics as a driver of more informed, data-based decision-making.

The global perspective suggests that predictive analytics, regardless of sophistication, represents a critical mechanism for bridging gaps between resource availability and organizational needs. Developed countries refine predictive accuracy, while developing regions prioritize accessibility and applicability, reflecting a convergence in recognizing its significance but a divergence in implementation strategies. This duality illustrates the contextual dependence of predictive analytics, where its role is equally transformative but manifests in ways that reflect distinct local capacities.

The Influence of Digital Twins on Smart Manufacturing

Case studies illustrate the significant role of digital twins in advancing smart manufacturing, with emphasis on their integration within cyber-physical systems to enhance operational efficiency. Lee et al. (2020) provided a detailed analysis of digital twin implementation in manufacturing, showing that these systems facilitate seamless communication between components such as sensors and actuators. The ability to simulate real-time processes enables firms to optimize resource allocation, reduce downtime, and enhance predictive maintenance capabilities. These benefits highlight digital twins as a vital technology for driving the next generation of manufacturing practices.

Further evidence from Proto et al. (2020) emphasized that predictive maintenance frameworks leveraging digital twin technology result in tangible financial benefits, particularly in logistics and service delivery. By addressing maintenance issues proactively, organizations can avoid costly failures, optimize production cycles, and ensure continuity in service delivery. These findings reinforce the argument that digital twins represent more than a technological novelty; they are a strategic asset with measurable contributions to operational resilience and cost savings.

International comparisons reveal a nuanced landscape of digital twin adoption. In developed nations such as Germany and the United States, digital twin systems are increasingly integrated with artificial intelligence and machine learning, enabling highly advanced predictive models for manufacturing processes. Schöggl et al. (2023) reported that these technologies support both operational efficiency and sustainability objectives, particularly through circular economy practices. These sophisticated models reflect a convergence of technological capability and strategic vision in advanced manufacturing sectors.

In contrast, developing economies encounter barriers that limit the widespread adoption of digital twin technologies. Infrastructure limitations, high costs, and limited access to technical expertise often confine these regions to foundational models of digital twin application. While manufacturers in these contexts may adopt basic digital twin frameworks, the lack of resources prevents full integration with advanced predictive systems. This divergence illustrates how structural and financial disparities shape the readiness to implement complex digital ecosystems.

Despite these challenges, the adoption of digital twins in developing regions is gradually increasing, driven by the recognition of their potential to enhance competitiveness. Emerging economies are experimenting with incremental approaches, often adapting simplified models to local contexts and gradually building capacity for more advanced implementations. This gradual convergence suggests that while disparities persist, there is a global trajectory toward the broader adoption of digital twins in manufacturing.

The comparative evidence therefore highlights both convergence and divergence in digital twin adoption across nations. Convergence is evident in the shared recognition of digital twins as transformative for manufacturing, while divergence reflects the degree of sophistication and integration achievable in different contexts. These findings emphasize the importance of tailoring digital strategies to local capacities, acknowledging that while developed nations lead in integration, developing countries are innovating adaptive models suited to their specific needs.

Overall, the findings confirm that big data and related digital technologies have transformative effects on organizational outcomes, predictive analytics, and smart manufacturing. The evidence demonstrates that developed nations predominantly deploy advanced frameworks, supported by extensive resources and infrastructure, while developing regions adopt more accessible models tailored to local contexts. Despite differences in sophistication, both contexts illustrate significant gains in productivity, efficiency, and resilience, underscoring the global relevance of big data. By comparing empirical findings, predictive evidence, and case studies, this review highlights the dual trajectories of convergence and divergence, offering critical insights into how big data can be harnessed across diverse economic and organizational landscapes.

The findings of this review align strongly with previous scholarship, reinforcing the widely acknowledged transformative role of big data across sectors while simultaneously exposing systemic and contextual barriers that constrain its adoption. Literature consistently emphasizes that big data enhances organizational outcomes, enabling more efficient decision-making and operational optimization. Jin et al. (2024) highlighted the reliance of organizations on data-driven insights, supplanting conventional intuition-based practices, which aligns with earlier theoretical frameworks positioning big data as a critical driver of competitiveness and innovation in the digital economy (Warner & Wäger, 2019). This convergence suggests that big data is not merely an auxiliary tool but an indispensable element of contemporary organizational strategies.

However, the evidence also reveals areas of divergence, particularly concerning the extent to which small and medium-sized enterprises (SMEs) are able to benefit from big data adoption. Coleman et al. (2016) emphasized the persistent challenges SMEs face, including resource limitations, high costs, and lack of skilled expertise, which often inhibit their capacity to adopt advanced analytics. These observations conflict with the more optimistic accounts of big data's universal transformative potential. Such findings underscore the importance of acknowledging heterogeneity across organizational types, where large corporations with greater financial and technical resources are better positioned to harness data-driven capabilities compared to SMEs and firms in developing economies (Rees et al., 2022). This divergence highlights that the benefits of big data adoption are not evenly distributed, requiring more nuanced frameworks that account for structural disparities.

The case of predictive analytics frameworks, such as the one successfully implemented by PETRONAS, provides a compelling example of big data's potential in optimizing operations and improving risk management (Sia et al., 2024). Yet, the replicability of such success stories is not guaranteed across sectors or regions. Industries with limited infrastructure, underdeveloped digital ecosystems, or insufficient technical expertise may not achieve comparable results. This indicates that while big data initiatives can produce significant organizational benefits, their impact is highly contingent upon contextual readiness. The variation also resonates with Schöggl et al. (2023), who noted that while developed economies advance in refining digital strategies, developing regions are still grappling with foundational challenges of infrastructure and resource accessibility.

Systemic and structural factors play a crucial role in shaping these disparities. Lack of infrastructure remains a significant barrier, particularly in developing economies where inadequate connectivity, outdated hardware, and weak cybersecurity frameworks hinder effective big data integration (Lee et al., 2020). Skill shortages compound these challenges, as both developed and developing countries report mismatches between academic training and industry requirements for data analytics expertise (Mathivanan & Jayagopal, 2020). For SMEs, limited budgets and lack of access to specialized training exacerbate the difficulty of cultivating data literacy, leading to unequal readiness across organizational scales (Coleman et al., 2016). Cultural resistance is another pervasive barrier, with entrenched business practices and skepticism about new technologies delaying digital adoption in both developed and developing contexts (Schöggl et al., 2023). Such organizational inertia highlights that technical solutions alone are insufficient without addressing the human and cultural dimensions of technological transformation.

Despite these challenges, several enabling factors support the adoption of big data in diverse contexts. Policy initiatives aimed at promoting digital literacy, expanding broadband infrastructure, and subsidizing technology adoption have proven effective in facilitating digital transformation. Public sector investments in digital infrastructure, for example, create shared platforms upon which private organizations can build capacity for big data utilization (Rees et al., 2022). Cross-sector collaboration further strengthens adoption pathways, as partnerships between academia, industry, and government foster knowledge transfer and align educational programs with labor market needs (Damian et al., 2019). These collaborations help cultivate a workforce capable of meeting the demands of data-intensive industries, mitigating the skill shortage barrier that remains pronounced worldwide.

Policy frameworks and institutional strategies are emerging as critical tools for addressing the hurdles of big data adoption. Maturity models tailored for SMEs provide structured pathways for assessing organizational readiness and gradually building analytics capabilities (Coleman et al., 2016). These frameworks recognize the unique constraints of smaller organizations and allow for phased adoption strategies that align with resource availability. At the regulatory level, standards such as the General Data Protection Regulation (GDPR) in Europe illustrate how ethical considerations around data privacy and security can be embedded into business practices, building trust in data-sharing and governance processes (Whitman, 2021). While compliance poses challenges, the long-term benefits include greater accountability and resilience in data-driven ecosystems.

Institutional support through funding and incubator programs further reduces barriers for SMEs and start-ups. Franciosa et al. (2019) highlighted how targeted financial support enables resource-constrained organizations to experiment with big data solutions and innovate competitively. These initiatives are especially important in developing contexts, where financial limitations often represent the primary barrier to adoption. In such cases, grants and subsidized programs can catalyze innovation, bridging the gap between technological potential and practical implementation.

The discussion also draws attention to ethical and systemic complexities that persist despite these enabling frameworks. Data privacy, informed consent, and security remain pressing concerns, particularly in regions lacking robust regulatory protections. While developed countries contend with stringent compliance requirements, developing regions often lack legal safeguards altogether, leaving organizations vulnerable to misuse and exploitation (Taifa & Nzowa, 2025). This imbalance highlights the need for globally informed frameworks that ensure equitable protections while allowing flexibility for localized implementation. Moreover, the uneven global distribution of data resources raises questions of digital inequality, as countries with advanced infrastructure consolidate advantages while marginalized communities continue to face exclusion from the benefits of big data adoption (Coleman et al., 2016).

Another critical dimension is the role of systemic enablers in driving inclusivity. Cross-sectoral approaches that integrate local knowledge, technological resources, and community-based initiatives can mitigate the exclusion of rural and underserved populations. For instance, SMEs in Southeast Asia have leveraged social networks and simple analytics to enhance competitiveness, demonstrating that even basic applications of big data can generate meaningful benefits when aligned with contextual needs (Alam et al., 2022). This suggests that policy interventions should not only focus on advancing cutting-edge applications but also on expanding accessibility to foundational tools that can empower marginalized groups.

While the current synthesis advances understanding of big data adoption, limitations in the existing body of literature constrain the comprehensiveness of the analysis. Comparative empirical studies between developed and developing countries remain limited, leaving critical questions about contextual differences inadequately explored (Rees et al., 2022). Longitudinal research assessing the sustained impact of big data adoption is also scarce, with most studies providing short-term evaluations that may not capture the full scope of transformation (Taifa & Nzowa, 2025). Furthermore, SMEs and rural communities continue to be underrepresented in the literature, creating blind spots that impede the design of inclusive frameworks (Coleman et al., 2016; Lainjo, 2019). Addressing these gaps requires future research to prioritize underexplored contexts and adopt more integrative frameworks that bridge technological, organizational, and societal dimensions of big data adoption.

The findings from this review therefore resonate with the broader literature while also pointing toward areas of unresolved tension and overlooked complexity. By situating big data adoption within systemic, structural, and cultural contexts, this discussion emphasizes that successful implementation requires more than technological capability—it demands deliberate strategies that integrate infrastructure development, skill cultivation, cultural adaptation, and regulatory safeguards.

CONCLUSION

This review highlights both the promise and the uneven reality of big data adoption. Its transformative potential is clear, but persistent barriers—particularly among SMEs and developing economies—underscore the need for inclusive strategies. Policy frameworks, cross-sector partnerships, and targeted capacity-building must be prioritized to ensure that benefits are broadly shared. Future research should move beyond short-term evaluations and conduct longitudinal, comparative studies that illuminate the sustained impacts of big data. **By emphasizing inclusivity and methodological rigor, this study contributes a globally relevant framework for equitable digital transformation**.

REFERENCE

Abedsoltan, H. (2023). Covid-19 and the chemical industry: impacts, challenges, and opportunities. *Journal of Chemical Technology & Biotechnology, 98*(12), 2789-2797. https://doi.org/10.1002/jctb.7531

Alam, K., Ali, M., Erdiaw-Kwasie, M., Murray, P., & Wiesner, R. (2022). Digital transformation among SMEs: does gender matter? *Sustainability, 14*(1), 535. https://doi.org/10.3390/su14010535

Amer, M., Radwhi, A., Ali, A., & Ali, A. (2022). An integrated digital collaborative work environment for drilling. https://doi.org/10.2523/iptc-22546-ea

Bhimavarapu, U. (2025). Building smart organizations leveraging power from emerging technologies in industry 5.0., 87-118. https://doi.org/10.4018/979-8-3693-9072-6.ch005

Brunet, M., Motamedi, A., Guénette, L., & Forgues, D. (2018). Analysis of BIM use for asset management in three public organizations in Québec, Canada. *Built Environment Project and Asset Management, 9*(1), 153-167. https://doi.org/10.1108/bepam-02-2018-0046

Chandratreya, A. (2025). Building a future-ready public sector cultural shifts in digital governance., 517-544. https://doi.org/10.4018/979-8-3693-6547-2.ch019

Charles, V., & Emrouznejad, A. (2018). Big data for the greater good: an introduction., 1-18. https://doi.org/10.1007/978-3-319-93061-9_1

Coleman, S., Göb, R., Manco, G., Pievatolo, A., Tort-Martorell, X., & Reis, M. (2016). How can SMEs benefit from big data? Challenges and a path forward. *Quality and Reliability Engineering International, 32*(6), 2151-2164. https://doi.org/10.1002/qre.2008

Damian, A., Piciu, L., Turlea, S., & Țăpuș, N. (2019). Advanced customer activity prediction based on deep hierarchic encoder-decoders., 403-409. https://doi.org/10.1109/cscs.2019.00074

Franciosa, P., Sun, T., Ceglarek, D., Gerbino, S., & Lanzotti, A. (2019). Multi-wave light technology enabling closed-loop in-process quality control for automotive battery assembly with remote laser welding., 9. https://doi.org/10.1117/12.2526075

Gacser, Z., Bourke, S., Hosszú, D., & Daniels, S. (2024). System change in practice: a report from the EHC think tank workstreams on access equity and future care pathways. *The Journal of Haemophilia Practice, 11*(1), 99-107. https://doi.org/10.2478/jhp-2024-0017

Gallese, C., Falletti, E., Nobile, M., Ferrario, L., Schettini, F., & Foglia, E. (2020). Preventing litigation with a predictive model of COVID-19 ICUs occupancy., 2111-2116. https://doi.org/10.1109/bigdata50022.2020.9378295

Garouani, M., Ahmad, A., Bouneffa, M., Hamlich, M., Bourguin, G., & Lewandowski, A. (2022). Using meta-learning for automated algorithms selection and configuration: an experimental framework for industrial big data. *Journal of Big Data, 9*(1). https://doi.org/10.1186/s40537-022-00612-4

Holroyd, C. (2019). Digital content promotion in Japan and South Korea: government strategies for an emerging economic sector. *Asia & the Pacific Policy Studies, 6*(3), 290-307. https://doi.org/10.1002/app5.277

Iftikhar, R., & Khan, M. (2022). Social media big data analytics for demand forecasting., 902-920. https://doi.org/10.4018/978-1-6684-3662-2.ch042

Jha, S. (2022). The counterfeit degree certificate: application of blockchain technology in higher education in India. *Library Hi Tech News, 40*(2), 20-24. https://doi.org/10.1108/lhtn-02-2022-0023

Jin, K., Zhong, Z., & Zhao, E. (2024). Sustainable digital marketing under big data: an AI random forest model approach. *IEEE Transactions on Engineering Management, 71*, 3566-3579. https://doi.org/10.1109/tem.2023.3348991

Khan, B., Naseem, R., Shah, M., Wakil, K., Khan, A., Uddin, M., … & Mahmoud, M. (2021). Software defect prediction for healthcare big data: an empirical evaluation of machine learning techniques. *Journal of Healthcare Engineering, 2021*, 1-16. https://doi.org/10.1155/2021/8899263

Koltes, J., Cole, J., Clemmens, R., Dilger, R., Kramer, L., Lunney, J., … & Reecy, J. (2019). A vision for development and utilization of high-throughput phenotyping and big data analytics in livestock. *Frontiers in Genetics, 10*. https://doi.org/10.3389/fgene.2019.01197

Kumar, V., Vijayakumar, V., Gupta, M., Rodrigues, J., & Janu, N. (2022). AI empowered big data analytics for industrial applications. *J.UCS - Journal of Universal Computer Science, 28*(9), 877-881. https://doi.org/10.3897/jucs.94155

Lainjo, B. (2019). Enhancing program management with predictive analytics algorithms (PAAS). *International Journal of Machine Learning and Computing, 9*(5), 539-553. https://doi.org/10.18178/ijmlc.2019.9.5.838

Lee, J., Azamfar, M., Singh, J., & Siahpour, S. (2020). Integration of digital twin and deep learning in cyber-physical systems: towards smart manufacturing. *IET Collaborative Intelligent Manufacturing, 2*(1), 34-36. https://doi.org/10.1049/iet-cim.2020.0009

Li, H., & Zhou, Q. (2023). Construction of digital capability evaluation index system for manufacturing enterprises. *Manufacturing and Service Operations Management, 4*(5). https://doi.org/10.23977/msom.2023.040512

Liao, R., & Feng, F. (2023). How do board network and academic connection promote digital transformation? *Kybernetes, 53*(11), 4592-4614. https://doi.org/10.1108/k-02-2023-0302

Lisnawati, L., Aryati, T., & Gunawan, J. (2024). Implementation of digital innovation on sustainability performance: the moderating role of green accounting in the industrial sector. *Eastern-European Journal of Enterprise Technologies, 1*(13 (127)), 59-68. https://doi.org/10.15587/1729-4061.2024.298639

Mathivanan, S., & Jayagopal, P. (2020). Recent development in big data analytics., 1640-1663. https://doi.org/10.4018/978-1-7998-7705-9.ch072

Mosch, L., Poncette, A., Spies, C., Weber-Carstens, S., Schieler, M., Krampe, H., … & Balzer, F. (2022). Creation of an evidence-based implementation framework for digital health technology in the intensive care unit: qualitative study. *JMIR Formative Research, 6*(4), e22866. https://doi.org/10.2196/22866

Müller, M., Vaseková, V., Kročil, O., & Kosina, D. (2024). Covid-19 as an advantage or a disaster? Crisis and change management strategies of Hong Kong social entrepreneurs during the pandemic. *Journal of Organizational Change Management, 38*(1), 25-58. https://doi.org/10.1108/jocm-02-2024-0101

Piciu, L., Damian, A., Ţăpuş, N., Simion-Constantinescu, A., & Dumitrescu, B. (2018). Deep recommender engine based on efficient product embeddings neural pipeline., 1-6. https://doi.org/10.1109/roedunet.2018.8514141

Proto, S., Corso, E., Apiletti, D., Cagliero, L., Cerquitelli, T., Malnati, G., … & Mazzucchi, D. (2020). Redtag: a predictive maintenance framework for parcel delivery services. *IEEE Access, 8*, 14953-14964. https://doi.org/10.1109/access.2020.2966568

Rahman, M., Ghazali, A., & Sawal, M. (2025). Exploring organizational factors of resistance to technology adoption in university libraries in Bangladesh. *Information Development.* https://doi.org/10.1177/02666669251325447

Rees, C., Hand, B., Carter, S., Bargeron, C., Cline, T., Daniel, W., … & Luikart, G. (2022). A framework to integrate innovations in invasion science for proactive management. *Biological Reviews, 97*(4), 1712-1735. https://doi.org/10.1111/brv.12859

Sarto, N., Bocchialini, E., Gai, L., & Ielasi, F. (2024). Digital banking: how social media is shaping the game. *Qualitative Research in Financial Markets, 17*(2), 348-369. https://doi.org/10.1108/qrfm-12-2023-0314

Schöggl, J., Rusch, M., Stumpf, L., & Baumgartner, R. (2023). Implementation of digital technologies for a circular economy and sustainability management in the manufacturing sector. *Sustainable Production and Consumption, 35*, 401-420. https://doi.org/10.1016/j.spc.2022.11.012

Sia, W., Ahmad, Z., Muhamad, S., Ali, A., & Hamdan, H. (2024). Effective risk management through data-driven HSE assurance program for safe execution project delivery. https://doi.org/10.2118/221994-ms

Sterrett, W., & Richardson, J. (2022). Innovation beyond the pandemic: the powerful potential of digital principal leadership. *Development in Learning Organizations an International Journal, 37*(2), 14-17. https://doi.org/10.1108/dlo-03-2022-0059

Subrahmanyam, S. (2025). Building a digital-first organizational culture., 101-124. https://doi.org/10.4018/979-8-3373-1005-3.ch004

Taifa, I., & Nzowa, J. (2025). Implementing supply chain management 4.0: potential driving forces and strategies from an empirical study of pharmaceutical industries. *Engineering Reports, 7*(6). https://doi.org/10.1002/eng2.70190

Tan, C., & Haji, M. (2017). Big data educational portal for small and medium sized enterprises (SMEs)., 11-15. https://doi.org/10.1145/3175684.3175688

Warner, K., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: an ongoing process of strategic renewal. *Long Range Planning, 52*(3), 326-349. https://doi.org/10.1016/j.lrp.2018.12.001

Whitman, M. (2021). Modeling ethics: approaches to data creep in higher education. *Science and Engineering Ethics, 27*(6). https://doi.org/10.1007/s11948-021-00346-1