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Exploring the Role of Machine Learning and Big Data Analytics in Enhancing Decision-Making Processes: A Systematic Literature Review

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***Abstract*—This Systematic Literature Review (SLR) analyzes the influence of Machine Learning (ML) and Big Data Analytics (BDA) on decision-making processes in several industries. The study aims to explore the potential of machine learning and big data analytics in enhancing decision-making, examining the tools and platforms used, and identifying the challenges encountered during deployment. Employing the PRISMA technique, 31 publications published from 2019 to 2024 were meticulously selected through a stringent screening process, using Scopus as the principal database. The results indicate that machine learning and big data analytics substantially enhance predictive accuracy, operational efficiency, and data privacy measures, while facilitating seamless integration with current systems. Furthermore, these technologies are becoming progressively accessible to Small and Medium Enterprises (SMEs). In the healthcare sector, machine learning models have exhibited a diagnosis accuracy of 99% in detecting breast cancer. Nonetheless, the report underscores other research deficiencies, particularly the necessity for more cost-effective solutions designed for SMEs. These limitations signify opportunities for future study to investigate ML and BDA applications in underexamined areas, such as logistics and manufacturing. This research highlights the necessity of creating economical, scalable, and industry-specific machine learning and big data analytics solutions to address existing difficulties. This systematic literature review (SLR) seeks to elucidate the function of machine learning (ML) and big data analytics (BDA) in decision-making, thereby assisting researchers and practitioners in enhancing the utilization of these technologies across many industrial applications.**

***Keywords*—Machine learning; big data analytics; decision-making; data privacy; PRISMA; SMEs.**

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I. INTRODUCTION

In recent years, machine learning and big data analytics have evolved into highly advanced tools for decision-making across numerous industrial sectors [1]. Machine learning and big data analytics are employed to handle extensive datasets, identify pertinent information, and facilitate strategic decision-making for organizations [2], [3]. As industries encounter rising worldwide demands and leverage advanced analytical tools, the integration of machine learning and big data analytics has emerged as a vital goal for attaining maximum performance and precise decision-making [4].

The capabilities of machine learning and big data analytics are most apparent in data-intensive industries like retail, banking, and healthcare, where extensive databases are utilized to enhance results. Electronic health records are utilized to improve pediatric care and facilitate prompt clinical decision support [5], [6]. In agriculture and transportation, predictive models have shown the ability of machine learning to enhance resource optimization and facilitate the advancement of infrastructure [7].

Notwithstanding its potential, the implementation of machine learning and big data analytics presents considerable hurdles. This encompasses the amalgamation of new technologies with legacy systems, apprehensions regarding data protection and security, and a deficiency of proficient individuals [8], [9]. Significant enhancements are urgently required in this technology, as numerous restrictions presently hinder the capacity of machine learning and big data analytics to demonstrate promise in the industry moving forward [10]. The swift progression of technology innovations introduces complexity, necessitating companies to adapt to maintain competitiveness consistently [10], [11], [12]. Mitigating these limitations is crucial to fully realize the potential of machine learning and big data analytics in decision-making processes.

This systematic literature review (SLR) aims to address these challenges by answering three key research questions:

- What opportunities do ML and BDA provide in adding insight to improve the decision-making process?
- What platforms, tools, and work systems have been used for machine learning and big data analysis?
- What are the current advancements and potential challenges in leveraging machine learning and extensive data analysis in decision-making?

This systematic literature review analyzes 29 pertinent articles to uncover emerging trends, research deficiencies, and practical insights for enhancing the incorporation of machine learning and big data analytics into decision-making processes across several industries [2], [13], [14]. This review enhances comprehension of the effective utilization of these technologies by examining prospects, assessing current platforms, and tackling difficulties. The findings aim to provide significant direction for academic researchers and industry practitioners in developing innovative methods to enhance decision-making through machine learning and big data analytics.

II. Materials and Methods

A. *Machine Learning and Big Data Analytics*

Machine Learning is an artificial intelligence that allows systems to learn from extensive data to make predictions or make decisions without a particular programming system [15], [16], [17]; machine learning itself is divided into three, namely:

1) Supervised Learning: This is a very commonly used technique, such as classification and regression, as a model is trained to predict something based on existing inputs [18]; many industries utilize supervised Learning to detect fraud or disease identification, such as the financial and health industries [19].

2) Unsupervised Learning: This method is usually used for unlabeled analysis, which looks for certain invisible patterns [20]. It is usually used to find anomalies in unusual purchasing activity or potential fraud in transactions. It is also used to segment customers based on purchasing behavior, demographics, and product preferences [21].

3) Reinforcement Learning: This training model makes decisions through testing feedback and actions. This has been tried in many fields, such as game development and autonomous vehicles or robots [22], [23].

Big Data Analytics (BDA) is a large and complicated collection of data beyond the capacity of traditional data processing [24], [25], [26]. When combined with ML, big data analytics can identify trends from large amounts of data, thus providing informative knowledge for businesses to make strategic decisions [18]. For example, in the retail industry, BDA helps segment customers, predict trends, and manage inventory. Also, BDA can analyze patient data in real-time, identify diseases, and design effective and efficient patient care in the health sector [27].

B. *Data-Driven Decision Making*

Databased decision-making is understanding obtained from the results of data analysis. ML and BDA play a vital role in this process, and the use of data is needed to make accurate predictions, divide resources fairly, and formulate strategies for the company going forward [28]. For example, e-commerce businesses use data-based decision-making to examine customer demographics and improve customer experience and Logistics companies can optimize effective routes to reduce operational costs through data analysis [29].

C. *Platforms and Frameworks for ML and BDA Implementation*

Building a machine learning model requires effective implementation of ML and BDA, such as infrastructure capable of processing extensive data; tools such as Apache Spark and TensorFlow are used to build sophisticated models [30], [31]. ApacheSpark is good at processing extensive data, and TensorFlow provides a systematic framework to strengthen machine learning models, especially for applying deep learning [15].

Also, analytical tools such as Google Cloud AI and Amazon Sagemaker provide structured answers to help businesses deploy and manage ML models easily [32]. These analytical tools provide the effectiveness needed for data processing in making real-time and accurate decisions; with this, companies can implement ML and BDA without expensive investments in extensive infrastructure [15].

D. *Related Surveys*

The closure of ML and B.D.A. is exciting because it supports valuable decision-making research [33]. Several studies have explored frameworks and methodologies to run this technology effectively and efficiently in the future in many industries such as agriculture, finance, and health [29]. However, many problems still need to be solved, namely, integrating ML and B.D.A. into existing systems and ensuring that data is distributed correctly [34]; there is still a need for more people in this field, hence the slow implementation of this technology [15].

To address this issue, further research is necessary to investigate the gap in enhancing the effectiveness of ML and BDA applications in business processes. The following table presents the survey results from systematic observations, highlighting key features and their contributions.

TABLE I
Summary of Retrieved Past Related Reviews

Studies	Features
[35]	Examine the role of augmented analytics in building digital transformation in various industries.
[36]	Proposed a weighted nearest-neighbor method with mutual information for the imputation of clinical data in the healthcare sector.
[37]	Searched for business intelligence solutions in Industry 4.0, focusing on modern business needs.
[38]	Figure out construction project performance using existing data, where significant profit margins are based on multiple projects.
[39]	Studied the application of machine learning in agricultural supply chains and identified the utility of artificial intelligence to improve operational efficiency
[40]	Learn machine learning to analyze real-time data in business, with the importance of data cleaning processes and exploratory data analysis.

Table I summarizes several studies on the application of ML and B.D.A. in various industries, where these studies involve several topics, for example, the role of augmented analytics in digital transformation, as well as nearest-neighbor methods to fill in missing data in the health sector and also B.I. solutions for industry 4.0, other research also explores construction project performance using previous data, utilizing ML in supply chains for agriculture which will be very efficient, of course, real-time data cleaning and analysis, in essence, this research shows the many ways ML and B.D.A. can be applied in many industries, by looking at challenges such as connecting technology and quality data for advanced study.

It shows that many studies focus on sectors with more advanced technological infrastructure, such as finance and health, but there are still many other sectors, such as manufacturing and logistics, that are still not widely explored; for example, many studies show that ML and B.D.A. are adopted because of operational and volume needs. This is large, but sectors such as logistics still have significant challenges in technology integration, as well as many ethical and data privacy issues. Many studies focus solely on health, but other industries face a research gap in this sector. Overcoming challenges like system integration and handling complex data requires further study.

E. Research Gap

The amount of research related to ML and B.D.A. has developed rapidly. However, there is still a research gap in various industries, many of which focus on technological infrastructure such as health, finance and agriculture. However, many sectors, such as manufacturing, logistics, and SMEs, have not been explored [35], [39], [41]. This requires further research to understand ML and B.D.A. that can be applied in industry, such as integration with existing systems or infrastructure limitations [36], [42].

Research related to data privacy in ML and B.D.A. is still limited in the health industry [35], [43]. Although regulations such as G.D.P.R. and C.C.P.A. have raised awareness regarding data privacy, there is still not much research discussing privacy in other sectors, such as logistics [15], [44]. Increased demand for personal data and the development of strong work related to ethics and data privacy are urgently needed [35], [43].

There is also little research regarding platforms and tools in ML and B.D.A., much of which focuses on advanced infrastructure, but many cheaper and more effective solutions for S.M.E.s remain unexplored [39]. Many studies are related to ML and B.D.A. frameworks in new industries, such as IoT and smart cities, even though this industry has excellent potential for increasing operational efficiency [45], [46]. Managing real-time data to make decisions is increasingly crucial in industries such as healthcare, logistics, and e-commerce, but ML and B.D.A. research addressing this is still limited [8], [46]. Finally, is partly specific with no explanation for other sectors. This limits opportunities for adaptation from one industry to another [39], [41].

F. Procedure

This systematic literature review follows the methodology of Moher et al. [44]. This SLR aims to collect and study studies on the application of ML and BDA to increase insight into data-based decision-making processes in various industrial sectors.

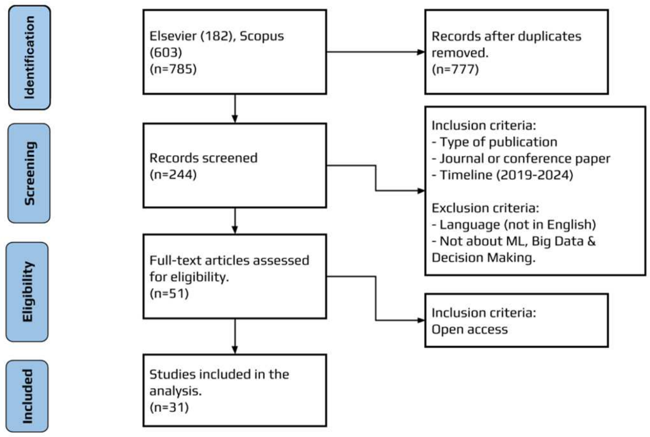

Fig. 1 PRISMA

In analyzing the answers to the research question, we established a clear framework and searched the central academic database, PRISMA. In PRISMA, there are Identification, Screening, Eligibility, and Inclusion, which are usually used for systematic studies. Figure 2 shows the Prisma methodology used.

G. Search Strategy and Data Collection

1) Determination of research questions and keywords: When finished determining the research question and keywords, the first step is to identify, namely searching, using the Publish or Perish, which links to the Scopus index to look for related studies. When searching for combinations of keywords, using AND and OR ensures a detailed and systematic literature search.

TABLE II
KEYWORDS

"Business Analytics"
OR
"Data Driven Decision"
OR
"Big Data"
OR
"Business Decision"
AND
"Machine Learning"

The combined keywords searched in Table II show 785 journal articles and conference papers. These documents will be explained further for research.

2) Screening and Eligibility: The second stage of the PRISMA method involves a rigorous screening process to eliminate unrelated and duplicate articles, ensuring that only high-quality and relevant studies are included for analysis. This stage is critical to maintaining the integrity of the systematic review and ensuring the accessibility of in-depth research. The process is as follows:

- Duplicate Removal. All papers imported into Mendeley are systematically checked for duplicates using the software's built-in tools. This step ensures that each study included in the analysis is unique and avoids redundant entries that could skew the results.

- Inclusion and Exclusion Criteria. After duplicates are removed, the remaining articles are filtered based on defined inclusion and exclusion criteria. These criteria are developed to align with the research objectives and may include factors such as publication date, language, relevance to the research questions, study design, and the availability of full-text access.
- Data Screening Process. The titles and abstracts of the filtered articles are reviewed to identify studies that meet the inclusion criteria. Articles that do not provide sufficient information or are unrelated to the research scope are excluded at this stage.
- Full-Text Review and Quality Assessment. For studies that pass the initial screening, a full-text review is conducted to ensure they meet the quality standards required for the systematic review. Quality assessment criteria are applied, such as the clarity of research methodology, robustness of data analysis, and relevance of findings to the research questions.

TABLE III
INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	Exclusion Criteria
Journal article or conference paper	Not a journal article or conference paper
Research journals published between 2019 and 2024.	Research journals published before the year 2019.
Open Access	Not Open Access
Related to ML, Big Data and Decision Making	Not Related to ML, Big Data, and Decision Making
Research journals contain complete information.	Research journal that does not have an abstract or any other information

After carrying out the inclusion and exclusion criteria, as seen in Fig 4, the initial collection of journal articles or conference papers was 785 to 244. An open access inclusion filter was carried out until the final number was 51. The selected papers were deemed to be the most relevant and suited to the research question being asked.

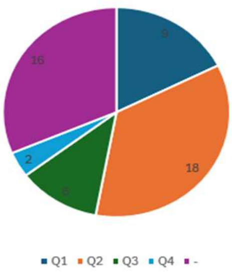

Fig. 5 Quartile distribution for 51 articles

In the 51 Papers, before being analyzed, the researchers also checked the Scopus rank first; as seen in Figure 5, there were 9 Q1s, 18 Q2s, 6 Q3s, 2 Q4s, and 16 of those without quartiles, so the researchers can filter whether the quality of the papers is good or not.

H. Selection of relevant studies

Stage 3 is the application of exclusion criteria; all journals that have nothing to do with ML, BDA, or decision-making will be removed, and in this stage, all titles, abstracts, and keywords will be checked for the suitability of papers that will pass to the advanced stage, after eligibility will be resulted in 51 papers for further review, and after studying them, the researcher decided that 31 papers would be selected for study because these papers were most relevant to the research objectives and thus provided valuable understanding for this research.

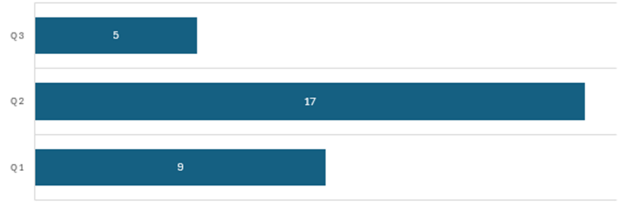

Fig. 6 Quartile distribution for 31 articles

Other criteria apart from the papers being relevant to the research, as illustrated in Fig. 6, the papers are also included in Scopus Q1 - Q3, which shows that the publication to be researched is of high quality and has gone through a strict review process; therefore, what will be analyzed is excellent and credible.

I. Limitations and Threat to Validity

In every study, there must be limitations; several factors when conducting research must be considered for evaluating this systematic literature review, several factors that can influence the findings, including:

- Language Bias: This S.L.R. only contains research in English, which is disadvantageous if the research is relevant but in another language.
- Limited access: This S.L.R. has restrictions on open-access journals or conferences, which usually require a fee, thereby limiting the research that can be accessed.
- Limited time: This S.L.R. only accesses research published 2019-2024, with nothing under 2019, meaning the analysis may be too basic and not detailed and comprehensive.
- Limited database: the selected papers are taken from the Scopus database only, which means that databases in other indexes are still not considered.

III. RESULTS AND DISCUSSION

The results of the Research are a critical analysis that can be implemented and have research limitations that will be included to provide a more comprehensive understanding. Table IV is the relationship between research questions and the 31 reviewed articles.

TABLE IV
RELATIONSHIP WITH RESEARCH QUESTIONS

RQ	Studies
1	[7], [8], [34], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66]
2	[7], [29], [34], [35], [49], [50], [57], [58], [59], [61], [62], [63], [65]
3	[8], [15], [29], [35], [43], [47], [48], [51], [53], [54], [55], [56], [60], [64], [66], [67], [68]

A. RQ1: What opportunities do ML and BDA provide in adding insight to improve the decision-making process?

1) Opportunities in the healthcare industry:

Machine learning (ML) has demonstrated significant potential in enhancing decision-making in the healthcare industry, particularly in disease diagnosis. For instance, a study on breast cancer detection using deep learning achieved an impressive accuracy of 99.8% [56]. Another related study, Explainable AI for Breast Cancer, introduced visualization tools like rainbow boxes and scatterplots to interpret deep learning models. These advancements illustrate how ML accelerates diagnostic processes, reduces dependency on manual diagnosis, and minimizes errors that could arise from traditional methods [56].

Nevertheless, challenges related to data privacy remain a critical issue in healthcare. Although solutions like differential privacy offer promising methods for safeguarding patient data, further research is needed to ensure these methods maintain model performance without compromising data security [35]. Furthermore, the use of Explainable AI (XAI) in medical diagnostics has proven crucial in fostering trust among doctors and patients [48]. Transparency in ML models directly addresses the research gap concerning the limited application of ML and BDA in healthcare, particularly regarding data privacy and trust.

This addresses the research gap, which highlights limitations in applying ML and B.D.A., particularly concerning data privacy in the health sector. Many limitations of research in this field are that it uses closed and not general datasets, which makes further research difficult to carry out outside the laboratory [54].

2) Opportunities in the Financial Sector:

Big Data Analytics (BDA) presents significant opportunities to improve data-driven decision-making in the financial sector. For example, the boosted trees algorithm has shown the ability to predict financial markets in real-time with up to 90% accuracy [59]. Studies using A Boosted Tree-Based Predictive Model for Business Analytics show that this model is adequate for analyzing historical data and trends, which can provide accurate insights in making investment decisions [29]. This method aligns with the need for sophisticated predictive tools in the financial sector, addressing research gaps related to accurate, real-time market analysis [35].

In practice, this solution can be implemented by large financial companies that have sufficient resources and technology. Companies with large infrastructures can use this predictive model to make investment decisions in real time [65]. While large financial companies benefit from these models due to their substantial resources and infrastructure, SMEs (Small and Medium Enterprises) face barriers such as high costs and limited technical expertise [50]. To address this disparity, cloud-based solutions such as Machine Learning as a Service (MLaaS) provide an affordable alternative for SMEs. By utilizing MLaaS, companies can leverage big data without investing heavily in infrastructure, making these tools accessible to smaller firms [67].

3) Opportunities in the Logistics Sector:

Machine learning has demonstrated significant potential in improving supply chain efficiency, particularly in real-time risk detection. For instance, combining ML and IoT sensors achieved 97% accuracy in predicting sudden fires in agricultural warehouses [7]. The research also combines IoT sensors to collect real-time data, which ML will analyze to check for anomalies that pose a fire risk [46].

Despite these promising results, most studies are conducted in controlled environments, limiting the generalizability of findings to real-world settings [61]. In real-world logistics, factors such as environmental conditions, warehouse size, and operational complexities may affect ML prediction accuracy [8]. Addressing these challenges will require further testing in diverse and dynamic settings.

In overcoming this limitation, further research is needed in real-world conditions to validate the application of ML in the logistics industry. Future research should prioritize large-scale, real-time testing of ML applications in logistics to validate their effectiveness in complex environments. This would provide stronger evidence for adopting ML in risk prediction and prevention within the supply chain [60].

B. RQ2: What platforms, tools and work systems have been used for machine learning and big data analysis?

1) Platform for Real-Time Analytics:

Cloud computing platforms are essential for implementing machine learning (ML) and big data analytics (BDA) in diverse industries. Due to its adaptable capacity and significant scalability, systems such as Microsoft Azure and IBM Cloud have become essential for major enterprises in handling extensive datasets. The study "Digital Transformation in Healthcare: Assessing the Role of Digital Tools" illustrates that these platforms facilitate data analysis accessibility in healthcare while also improving operational efficiency and aiding precise decision-making in various industries [62].

Although these platforms offer significant advantages for large businesses, they pose issues for small and medium enterprises (SMEs) due to their high costs. Open-source alternatives such as Hadoop and Apache Spark offer cost-effective solutions; nonetheless, they necessitate enough resources and proficient individuals for optimal implementation. The research titled Machine Learning-Based ABA Treatment for Autism underscores a prevalent challenge: the scarcity of skilled professional's adept at effectively utilizing these tools, which hinders the extensive implementation of ML and BDA technology [43]. As a practical solution, SMEs can leverage Machine Learning as a Service (MLaaS) to access advanced technologies without the need for extensive infrastructure. MLaaS platforms reduce operational burdens by offering cloud-based ML tools, making them a viable option for smaller enterprises seeking to harness the benefits of ML and BDA [46].

2) Tools for Data Management at Large Scale:

Technologies such as Apache Spark and Hadoop are extensively utilized in the management of big data across several industries, especially for large-scale data processing. Hadoop has demonstrated efficacy in processing historical data within the manufacturing industry, resulting in enhanced operational efficiency. The journal Real-Time High-Load Infrastructure Transaction Processing exemplifies Hadoop's capacity to manage intricate massive data, facilitating expedited and precise analyses [60].

Furthermore, TensorFlow and PyTorch are frequently employed for the development of machine learning models in sectors like healthcare and manufacturing. The paper "Machine Learning for Intelligent Data Analysis" demonstrates how these tools improve the creation of predictive models, particularly in sectors such as manufacturing and logistics, where precise data analysis is essential for process optimization [61]. Nonetheless, the utilization of these tools by SMEs is constrained due to the requisite specialist skills. Numerous small firms face challenges due to a deficiency of experienced people required to manage and apply these technologies effectively. To bridge this gap, SMEs can contemplate implementing user-friendly platforms or training initiatives aimed at enhancing proficiency in these products. Furthermore, cloud-based solutions designed for small enterprises may facilitate equitable access to big data management technology, allowing SMEs to compete more effectively with larger corporations [49].

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C. RQ3: What are the current advancements and potential challenges in leveraging machine learning and extensive data analysis in decision-making?

11

1) Developments in Machine Learning and Big Data Analytics:

Recent improvements in machine learning (ML) and big data analytics (BDA) have markedly improved their efficacy, particularly in handling extensive datasets and enhancing model precision. The advent of tools such as TensorFlow and PyTorch has facilitated the creation of more advanced and accurate machine learning models, as noted in the journal Machine Learning for Intelligent Data Analysis [46]. These tools have accelerated the adoption of deep learning techniques, which are increasingly used for anomaly detection and predictive analytics across various sectors, such as healthcare, finance, and logistics [62].

7

The most significant development is Federated Learning, which can train ML models on multiple data sources without compromising privacy. The journal Digital Transformation in Healthcare explains that Federated Learning has overcome the data privacy problem and allows the data to remain at the source. The model is trained collectively [63]. Additionally, advancements in cloud computing, with platforms like Amazon AWS and Google Cloud, have revolutionized ML and BDA applications, providing scalable and accessible solutions for businesses [69].

2) Challenges in data privacy:

1

Data privacy continues to be a key issue in the implementation of machine learning and big data analytics, especially in sensitive sectors such as banking and healthcare. The study Intelligent Feature Selection with Deep Learning for Financial Risk Management emphasizes privacy issues in the management of personal financial data, claiming that data security is an essential barrier to technology adoption [7]. Additionally, the healthcare sector encounters difficulties in protecting sensitive patient information, a significant research deficiency [8].

To address such challenges, methodologies such as differential privacy and federated learning have been suggested. Federated learning provides an effective solution by preserving data privacy while facilitating collaborative model training. Nonetheless, as indicated in the article Using Customer Knowledge to Explain Customer Behavior, the practical application of these methods necessitates more study to guarantee that model accuracy is not compromised [63]. This solution necessitates additional testing to confirm that data privacy can be assured, hence minimizing the accuracy of the resultant model [69].

Not only that, but data privacy regulations in each country are also increasingly complex. Some countries have strict regulations, such as the GDPR in the European Union, while others still need strong regulations [64]. The journal Stimulating Implementation of Sustainable Development Goals and Conservation Action states that variations in privacy regulations in many countries challenge companies to operate globally because they must comply with different rules in each country [68]. This is a challenge in adopting ML technology globally because they have to navigate various existing regulations.

3) Challenges in Technology Adaptation for SMEs:

Despite the opportunities offered by ML and BDA in enhancing decision-making, their adoption among small and medium enterprises (SMEs) remains limited. High costs, resource constraints, and a lack of skilled personnel are among the primary barriers. The journal Causal Discovery with Attention-Based Neural Networks notes that SMEs often struggle to integrate new technologies with existing systems due to insufficient technical expertise and infrastructure [60].

Furthermore, cloud and machine learning as a service (MLaas) solutions can be an option for S.M.E.s. For example, the journal Digital Transformation in Healthcare: Assessing the Role of Digital Tools shows that the MLaas model allows S.M.E.s to utilize this technology without having to invest expensively [46]; Nevertheless, this solution already exists, and the adoption rate is still low because awareness and knowledge among companies when making decisions is underutilized [46]. SMEs have many problems, such as data security and lack of technical skills, which increasingly hinder the widespread adoption of this technology [65].

4) Comparison of analysis results with related surveys:

This analysis discusses the application of ML and B.D.A. in various industries, agreeing with several related surveys. The survey examples related to augmented analytics and digital transformation align with the analysis discussed, namely MLaas and Cloud Computing as practical solutions for SMEs. However, a survey of general views regarding methodology and analysis goes deeper by providing detailed examples, such as using boosted trees in finance and deep learning for medical diagnosis. For example, boosted stress can increase prediction accuracy by up to 90%, greatly benefiting companies with the infrastructure to provide real-time analysis [59]. According to this analysis, through a paper I researched, deep learning can also diagnose breast cancer by up to 99.8%, which shows that the approach is accurate in medical diagnosis [56]. The related survey does not provide detailed impacts of this algorithm, so my analysis adds an original contribution regarding the use of this technology.

The nearest-neighbor method used by one of the related surveys for health data considerably broadens my analysis regarding data privacy in the health industry. Because the survey focused on technique, this analysis provides a better solution, such as federated learning, to maintain patient privacy, which is increasingly crucial due to the European Union's G.D.P.R. Federated Learning helps train ML models without changing patient data to centralized data so the data remains protected on the original server; this will reduce the risk of data leaks [62]. The other survey requires detailed explanations, whereas this analysis offers a fundamental understanding of how this technology can be implemented in real-world scenarios.

5) Identified Gaps:

The investigation identified multiple substantial research deficiencies. There is a significant deficiency of studies examining the implementation of machine learning and big data analytics in logistics, manufacturing, and small to medium-sized enterprises, underscoring the necessity for research in these inadequately researched domains. Secondly, the majority of current research is predominantly theoretical, lacking substantial real-world validation or extensive testing, hence limiting its practical usefulness. Third, although data privacy has been thoroughly examined in the healthcare sector, there is inadequate attention to privacy issues in other industries, such as logistics and retail. Fourth, studies on the application of machine learning and big data analytics for small and medium-sized enterprises are few, despite their significant contribution to global economies. The evolution of ML and BDA technologies frequently diverges from current legislation, highlighting the necessity for improved alignment between technology progress and legal structures.

6) Recommendations and Future Research Directions:

Future research should focus on ML and B.D.A. in industries that are yet to be widely explored. Apart from that, extensive field implementation studies are also needed to test the effectiveness of this technology in the real world. Research related to data privacy must be broad and appropriate to develop a cloud base to reach S.M.E.s that need it. Finally, there is a great need for collaboration between researchers and those making policies to unify regulations according to developments in ML and B.D.A. in various industries.

IV. Conclusion

This systematic literature review emphasizes the transformative capacity of machine learning (ML) and big data analytics (BDA) in improving decision-making processes across sectors like healthcare, banking, and transportation. The results highlight the substantial impact of machine learning and big data analytics on enhancing accuracy, productivity, and strategic decision-making. Significant progress encompasses predictive diagnostics in healthcare, which have exhibited exceptional success in anomaly identification and disease forecasting. Conversely, sectors like logistics are in the nascent phase of utilizing these technologies, offering significant potential opportunities.

Nevertheless, this analysis highlights significant difficulties that impede the broader deployment of ML and BDA, despite these achievements. Data privacy is an important issue, especially in sectors managing sensitive information, like finance and healthcare. The substantial expenses, intricacies, and integration challenges associated with ML and BDA systems provide considerable obstacles for Small and Medium Enterprises (SMEs), restricting their access to these transformative technologies.

Future research must focus on the extensive implementation of machine learning and big data analytics in underexplored sectors, including logistics, manufacturing, and small to medium-sized enterprises. There is an urgent need to develop cost-effective, scalable, and accessible cloud-based solutions tailored for SMEs. Subsequent investigations should include privacy-preserving technologies, like federated learning and differential privacy, to guarantee data security while maintaining performance. Furthermore, promoting collaboration among researchers, industry professionals, and politicians is crucial to synchronize technical progress with changing legal frameworks, especially concerning data privacy and security.

In conclusion, although machine learning and big data analytics have substantial prospects for enhancing decision-making across several sectors, considerable efforts are necessary to address prevailing difficulties. This study enhances academic knowledge by pinpointing research deficiencies and practical insights, presenting actionable recommendations for SMEs and policymakers, and delineating clear pathways for future research. Addressing these concerns will render the integration of ML and BDA more inclusive, impactful, and congruent with technological and legal advancements.

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